



UNIVERSITY OF GENOVA

PHD PROGRAM IN BIOENGINEERING AND ROBOTICS

**A protected discharge facility for the elderly:
design and validation of a working
proof-of-concept**

by

Chiara Martini

Thesis submitted for the degree of *Doctor of Philosophy* (31° cycle)

December 2018

Annalisa Barla and Francesca Odone
Giorgio Cannata

Supervisors
Head of the PhD program

Thesis Jury:

Francesco Isgro', *University of Naples - Federico II*
Henry Medeiros, *Marquette University*

External examiner
External examiner

Dibris

Department of Informatics, Bioengineering, Robotics and Systems Engineering

I would like to dedicate this thesis to 309

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Chiara Martini

March 2019

Acknowledgements

I want to say thank you to all the people that helped me both professionally as well as personally. First of all, Annalisa Barla and Francesca Odone, my supervisors, for their advice and continuous support. Thank to Alessandro Verri a master of science and life. Thank to Nicoletta Noceti and Manuela Chessa for all the work done to help me during the data analysis.

Thank to the E.O. Ospedali Galliera, in the figure of Gian Andrea Rollandi, the one who had the idea first, who enthusiastically managed to excite everyone and make the project achievable. Thank to Alberto Pilotto and Alberto Cella for the recruitment of volunteers, for the availability of time and energy provided to the project, for having instructed me on the qualitative medical evaluation and for guiding me in the evolution of the obtained results. Thank to Graziella Congiu for the patience and the support in recruiting volunteers for my experiments. Thank to Carlotta Patrone for the organizational and practical part of the project, with her and thanks to her we managed to organize all the steps of the project.

Thank to Nicolo' Casiddu and Silvia Pericu for the splendid work done in terms of design and architecture.

Thanks to all the volunteers that participate to the process of data acquisition, in particular thank to AVO - Associazione Volontari Ospedalieri (Hospital volunteers association) for their contribution.

Abstract

With the increasing share of elderly population worldwide, the need for assistive technologies to support clinicians in monitoring their health conditions is becoming more and more relevant. As a quantitative tool, geriatricians recently proposed the notion of *frail elderly*, which rapidly became a key element of clinical practices for the estimation of well-being in aging population. The evaluation of frailty is commonly based on self-reported outcomes and occasional physicians evaluations, and may therefore contain biased results.

Another important aspect in the elderly population is hospitalization as a risk factor for patient's well being and public costs. Hospitalization is the main cause of functional decline, especially in older adults. The reduction of hospitalization time may allow an improvement of elderly health conditions and a reduction of hospital costs. Furthermore, a gradual transition from a hospital environment to a home-like one, can contribute to the weaning of the patient from a condition of hospitalization to a condition of discharge to his home. The advent of new technologies allows for the design and implementation of smart environments to monitor elderly health status and activities, fulfilling all the requirements of health and safety of the patients.

From these starting points, in this thesis I present data-driven methodologies to automatically evaluate one of the main aspects contributing to the frailty estimation, i.e., the motility of the subject. First I will describe a model of protected discharge facility, realized in collaboration and within the E.O. Ospedali Galliera (Genoa, Italy), where patients can be monitored by a system of sensors while physicians and nurses have the opportunity to monitor them remotely. This sensorised facility is being developed to assist elderly users after they have been dismissed from the hospital and before they are ready to go back home, with the perspective of coaching them towards a healthy lifestyle. The facility is equipped with a variety of sensors (vision, depth, ambient and wearable sensors and medical devices), but in my thesis I primarily focus on RGB-D sensors and present visual computing tools to automatically estimate motility features. I provide an extensive system assessment I carried out on

three different experimental sessions with help of young as well as healthy aging volunteers. The results I present are in agreement with the assessment manually performed by physicians, showing the potential capability of my approach to complement current protocols of evaluation.

Table of contents

List of figures	xi
List of tables	xv
1 Introduction	1
1.1 Motivation	1
1.2 Problem definition and requirements	5
1.3 Contribution	6
1.4 Outline	8
2 State of the art	11
2.1 Introduction	11
2.2 How frailty is evaluated by geriatricians	14
2.2.1 The Comprehensive Geriatric Assessment (CGA)	15
2.2.2 The Multidimensional Prognostic Index (MPI)	16
2.3 Advantage and potential of continuous automatic assessment	18
2.4 Ambient Assisted Living	20
2.5 Smart homes	23
2.6 Technologies currently on the market	29
2.7 Open challenges of continuous automatic assessment	34
3 Mo.Di.Pro. Model of Protected Discharge	37
3.1 Introduction	37
3.2 Concept	38
3.2.1 Vision sensors	44
3.2.2 Virtual Reality based device for cognitive assessment	45
3.2.3 Health devices and distributed ambient sensors	47
3.3 Data Collection	51

4	Methods for automatic assessment	55
4.1	Introduction	55
4.2	Evaluating the motility of patients	57
4.2.1	Data acquisition, storage and preprocessing	57
4.2.2	Localization	59
4.2.3	Motility quantities estimation	59
4.2.4	Motility Index estimation	64
5	Experiments	67
5.1	Introduction	67
5.2	Preliminary assessment 1: health	68
5.3	Preliminary assessment 2: motility	72
5.4	Experiment 3: coherence of geriatric assessment and automatic assessment	77
5.5	Experiment 4: analyzing a larger group of active and healthy aging volunteers	84
5.6	Exploratory Data Analysis (EDA)	89
5.7	Overcoming the issues	92
6	Conclusion and future works	97
6.1	Main contribution	97
6.2	Final discussion	98
6.3	Future works	102
6.4	Publications	102
6.5	Oral presentations and Posters	103
Appendix A MPI		115
Appendix B TUG test		123

List of figures

1.1	Statistics of population over 65 worldwide over the years. Source https://data.worldbank.org/	2
1.2	MPI score versus length of hospital stay. MPI increases after the twelfth day of hospitalization, and it may overcome the score of the admission day in the acute phase (Volpato et al., 2016).	4
3.1	Third floor of the Galliera hospital, starting point of my project. The red line indicates the chosen area for the construction of the smart facility.	39
3.2	Apartment plan with description of the spaces.	40
3.3	(a) shows one of the two bedrooms, (b) shows the common room, (c) shows the kitchen and the table area, (d) shows the entrance of the apartment.	41
3.4	Apartment plan. Blue rectangles represent the RGB-D sensors, the small red squares correspond to the cameras. Green circles represent the localization tags, while purple rectangles indicate the Passive Infra-red (PIR) sensors and their field of view (through purple lines). They are all wired to the workstation (green square), placed in the gym.	42
3.5	The telepresence robot (PadBot P1), placed in the facility, allows guests and caregivers to communicate with doctors and nurses outside the apartment.	43
3.6	The joints recognized by the Asus RGBD sensor and the OpenNI SDK. For each joint, the 3D position with respect the sensor, and according to the axes highlighted in the figure, is computed.	46
3.7	A sketch of the visual sensors fields of view and their overlap. The left panel shows the field of view of the two cameras, while the right panel shows the field of view of the two RGB-D sensors.	46

3.8	A sketch of the "Supermarket" experimental setup, based on a standard tablet.	48
3.9	Vital monitoring devices. From left to right, clockwise: blood pressure monitor, glucometer, oximeter and smart phone	49
3.10	Example of iHealth app, figure (a) shows the SpO2 measure automatically recorded by the smartphone, and figure (b) shows the pressure measure.	50
3.11	Some of the sensors used. From top left, clockwise: (a) mini-dome camera, (b) ASUS Xtion Pro RGBD camera, (c) ELIKO KIO RTLS localization system, (d) SparkFun PIR Motion Sensor, (e) SparkFun Luminosity Sensor and (f) SparkFun Force Sensistive Resistor.	51
4.1	A visual sketch of the pipeline of my system. When the RGB-D sensors detect the presence on a human in the scene, they trigger the corresponding camera that starts the acquisition. Data are stored on-line in a database that makes them available for future off-line analysis.	56
4.2	An example of distribution of head joints positions over time. (a)The trajectories of head positions projected onto an image plane representing the environment (blue and red refer to $RGBD_1$ and $RGBD_2$, respectively). (b) A heat map obtained from the points distribution of head joints positions over time.	60
4.3	An example of temporal analysis of the head height (a) and its velocity (b). Posture and velocity changes are detected and used to identify tracks (c).	63
5.1	RiHealthy platform interface. The monthly calendar shows all the measures for each patient as orange squares. A detail is shown for a blood oxygen saturation measure.	69
5.2	Health data from two young volunteers, one male and one female during a week. Vertical lines indicate the day of the week. (a) Shows male blood pressure records , (b) shows female blood pressure records, (c) shows male SPO2 record, (d) shows female SPO2 records, (e) shows male weight records, (f) shows female weight records.	70
5.3	Pressure data from two elderly volunteers, one male and one female during a week. Vertical lines indicate the day of the week.	71

5.4	Screen shot of the mobile phone home, there are only three icons, one is the emergency call and the other two are the health devices app. On the right is shown the mobile phone unlock code.	72
5.5	The velocity estimated over time on a sequence where a subject walks at different speeds.	75
5.6	Comparison between manual annotation shown in table 5.7 (light blue) and automatic (dark blue) assessment shown in table 5.8 in terms of percentage of time spent standing still.	78
5.7	Comparison between manual annotation shown in table 5.7 (light blue) and automatic (dark blue) assessment shown in table 5.8 in terms of percentage of time spent sitting.	79
5.8	Comparison between manual annotation shown in table 5.7 (light blue) and automatic (dark blue) assessment shown in table 5.8 in terms of percentage of time spent moving.	80
5.9	Comparison between MPI and MI on the five healthy elder volunteers. Automatic evaluation MI produces a result that is very much in line with the qualitative MPI.	81
5.10	Number of state transitions evaluated as the average of TR_{2sit} and TR_{2st} and walk instances W for each volunteer ($\#v1$ to $\#v5$).	82
5.11	Longest walk distance and walk time for each volunteer ($\#v1$ to $\#v5$).	83
5.12	Cumulative analysis on the correlation between SPPB and MI on subsets of volunteers ordered by duration (duration is expressed in hours - e.g. 1 is 1 hour). See text for more details on how the plot is constructed	86
5.13	Histogram depicting a slow patient	90
5.14	Histogram depicting a rapid patient	90
5.15	Histograms depicting a patient that spent most of the time still.	91
5.16	PCA performed with ADENINE on the data of 24 healthy elder volunteers (Experiment 3). Each patient is associated with the date he/she visited the facility and with a random color coding. PCA analysis allowed us to identify one person whose habits deviate from common behavior.	93

- 5.17 t-SNE performed with ADENINE on the data of 24 healthy elder volunteers(Experiment 3). Each patient is associated with the date he/she visited the facility and with a random color coding. t-SNE analysis allowed us to identify a set of data carrying a reduced amount of information with respect to the other. 94
- 6.1 Preliminary results in video analysis. Left: 2D pose estimation; center: pose classification; right: gaze direction estimation. 102

List of tables

2.1	Assistive Smart Home Projects	24
4.1	A summary of the mathematical formulation for the tracks analysis.	65
5.1	Summary description of the manually annotated sequences recorded in the monitored apartment. T_{sit} is the Time spent sitting, TS is the Time spent Standing and TM is the Time spent Moving	72
5.2	Quantitative analysis on the motility quantities performed on 5 annotated sequences. GT represent the ground truth, EST is the estimated value and ERR is the associated relative error.	73
5.3	Accuracies on transitions of posture or dynamics, for which I have a ground truth available. Each estimate is coupled with the corresponding ground truth value, and the associated relative error.	74
5.4	Estimates of statistics for which the ground truth is not available . .	74
5.5	Motility Index (MI) for the 5 subjects (see text for details).	76
5.6	Geriatric assessment on elderly volunteers. The table reports all the measures that contribute to the formulation of the Multidimensional Prognostic Index (MPI) and the MPI itself. In particular, I reported the Short-Portable Mental Status Questionnaire (SPMSQ), the Exton-Smith Scale (EES), the Activities of Daily Living (ADL), the Instrumental Activities of Daily Living (IADL), the Mini Nutritional Assessment (MNA), the number of drugs (Med.), the Cumulative Index Rating Scale (CIRS) and the Short Physical Performance Battery (SPPB). . . .	77

5.7	Evaluation of 5 elderly subjects in good health: summary of the geriatric assessment, in terms of gait speed measured during the test of a 4 meters walk. The last three columns report a coarse manual annotation carried out by the author by visually inspecting video sequences.	78
5.8	Automatic evaluation of 5 elderly subjects in good health: the observation time, the estimated percentage of time spent standing still, sitting, or walking, the estimated average speed, and the overall estimated Motility Index (MI).	84
5.9	Pearson correlation coefficients among the parameter computed by the "Supermarket" test and the GPCog results. *p<0,05; **p<0,001 . . .	88

Chapter 1

Introduction

This chapter explains the motivations that led to the realization of the model of protected discharge and my contribution within it. With the increasing share of elderly population worldwide, the need for assistive technologies to support clinicians in monitoring their health conditions is becoming relevant. Aging leads to an increase in the frailty of the person and a loss of autonomy. For this reason, in my work I focused on a system for the continuous and automatic monitoring of frailty of the elderly.

The chapter is organized as follows, in Section 1.1 I will outline the reasons that led me to the realization of the project, I will define the problem and the requirements for its realization (Section 1.2), and I will conclude with my contributions in Section 1.3.

1.1 Motivation

According to the World Bank, Italy has the second-highest share of population aged over 65 worldwide, i.e., 23% in 2016, and statistics related to G20 countries are becoming increasingly similar (see Figure 1.1). Liguria, my region, is among the highest in this ranking.

Aging causes, in general, the reduction of the individual's potential, leading to a state of vulnerability and instability of the clinical conditions. As people age, there is an increasing risk to experience multi-morbidity which, lead to a reduction on the quality of life, an increase in hospitalization time and the risk of mortality. To highlight this condition, recent medical literature has proposed the notion of *frail*

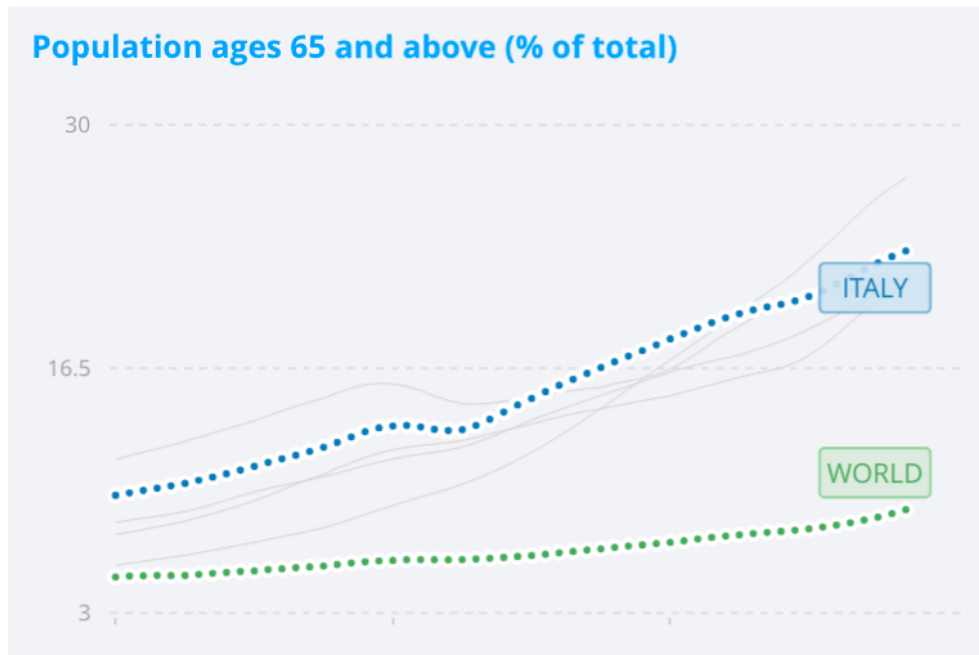


Figure 1.1 Statistics of population over 65 worldwide over the years. Source <https://data.worldbank.org/>

elderly, an individual with an elevated risk of complications that may result in loss of functional autonomy or death (Fried et al., 2004).

Frailty estimation Inspired by this definition of frailty, several methods have been proposed in clinical practice and research to estimate the overall clinical and functional status of the hospitalized older subjects (Dent et al., 2016). Among them, the Multidimensional Prognostic Index (MPI), based on a standard Comprehensive Geriatric Assessment (CGA) (Pilotto et al., 2008) showed very good accuracy and excellent calibration in predicting several negative health status outcomes as well as institutionalization, re-hospitalization and mortality (Angleman et al., 2015; Volpato et al., 2014; Warnier et al., 2016). The MPI score is based on the evaluation of the clinical, cognitive, functional, nutritional, and social domains, as defined in the International Classification of Functioning, Disability, and Health¹. However, all these proposed evaluations are derived from self-reported questionnaires and sporadic medical evaluations, so the index is prone to bias and based on episodic and not quantitative assessments. An objective and continuous evaluation of different dimensions would complement such clinical evaluations, leading to a reduction in

¹<http://apps.who.int/classifications/icfbrowser/>

the medical assistance, and a positive overall benefit on public healthcare (Martini et al., 2018a). Recently, with the advent of assistive technologies, various approaches for the automatic estimation of frailty have been proposed (Bathrinarayanan et al., 2013; Cao et al., 2009; Liu and Liu, 2010; Zouba et al., 2010).

Frailty and hospitalization Hospitalization is the first cause of functional decline in the elderly: indeed, 30 to 60% of elderly patients loose some independence in basic Activities of Daily Living (ADL) in the course of a hospital stay (Volpato et al., 2016). In fact, beside the disabling effect of the acute event, hospitalization itself might represent an additional stressor in terms of environmental hazard, reduced caloric intake, low physical activity or prolonged bed-rest, depressed mood and social isolation. Prolonged hospital stays may increase the risk of infections and other iatrogenic complications, worsen the patient quality of life especially in the elderly, and imply a waste of economic and human resources (Lafont et al., 2011; Volpato et al., 2007). In the worst case, these complications may lead to mortality (Volpato et al., 2016). Figure 1.2 shows prolonged hospital stays increase the frailty of the elderly. In particular, after the twelfth day of hospitalization, elderly patients worsen their conditions, risking to find themselves with a frailty index higher than at the time of their admission in the acute phase.

Recent studies conducted in various countries show that a significant proportion of hospital beds (about 8%) is indeed occupied by patients who experience a Delayed Hospital Discharge (DHD) (Lenzi et al., 2014). Among them, more than half (52.7%) spend extra time in hospital after recovery from acute condition. Delayed discharges may be regarded as an indicator of inefficient use of hospital beds. Factors associated with delayed hospital discharges have been attributed to patients' demographic, medical, family and dependency characteristics, as well as organisational and administrative processes. Elderly patients are more prone to have protracted hospital stay because they present multimorbidity or specific problems such as cognitive impairment or orthopaedic conditions that may require rehabilitation, domiciliary services or some form of institutional care that may not be immediately available at discharge. DHD also cause a waste of economic resources. In fact inefficient occupation of hospital beds increases hospital costs, one bed costs to the structure about 1000 Euros per day. The limitation of DHD patients is therefore an important objective both for patient's well being and for cost reduction. A large amount of

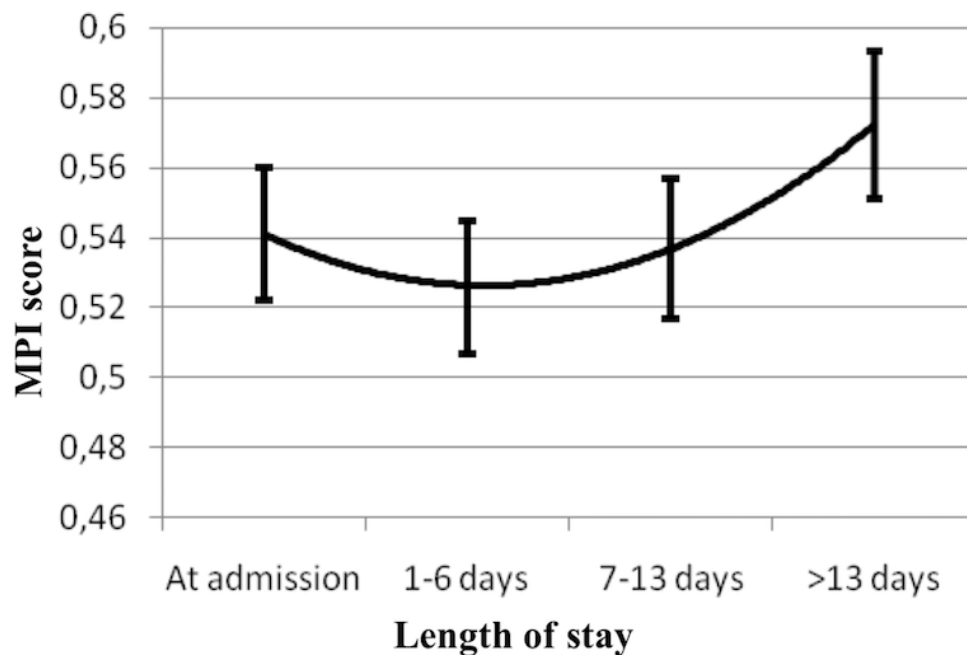


Figure 1.2 MPI score versus length of hospital stay. MPI increases after the twelfth day of hospitalization, and it may overcome the score of the admission day in the acute phase (Volpato et al., 2016).

DHDs might thus be avoided in the presence of smart home-like facilities, able to guarantee the appropriate level of assistance required for these typology of patients, but mitigating the human and financial efforts that a prolonged hospital stay would require. Technologies currently available offer now the possibility of putting in practice this concept.

Aging & Technology Since the reference patients of my project are the elderly, we must consider some aspects and issues related to the relationship between aging and technology. The mission is to contribute to the welfare of elderly people. In principle this is done by creating equal possibilities at the social and individual level to use technical devices and services. Technology not only completes human deficiencies, prevents, delays or compensates physical losses or the loss of social contacts, but it also has to be understood as an effort to study the potential benefits of technology from the elderly people's point of view.

Aging and Technology is an emerging multidisciplinary field. It seeks to enhance the interaction between elderly people and their environment in order to maintain the maximum level of sustained functional autonomy and independence. Technology

for elderly should be easy to use allowing them to benefit from it. The elderly usually see technology as a barrier, because of their physical or cognitive impairment. The main goal of research in technologies for the elderly is to create solutions that are simple, safe and user friendly.

1.2 Problem definition and requirements

There is an increasing necessity to create residences where some types of patients can find an intermediate space between the hospital stay and their home, in order to discharge them earlier with the efficiency of hospitalization turnover and more safety for the patient. As mentioned in Section 1, long hospitalization time is a pejorative element of the overall state of health of elderly patients. Furthermore, a gradual transition from a hospital environment to a home-like one, with all home automation security controls, can contribute to the weaning of the patient from a condition of hospitalization to a condition of discharge to his home. This type of new intermediate environment is a laboratory for telematic and domotic analysis, for various architectural and engineering solutions.

The technology already available is mature enough to allow the design and implementation of a monitoring system that may fulfill most of the general requirements of health and safety of patients. However, some of the requirements are extremely challenging and need to be carefully addressed in order to guarantee the expected results. The key and the most difficult requirements is the "seamless" and "unobtrusive" monitoring in order not to alter the life of vulnerable people that may or may not accept to wear sensors or behave in some unusual way in order to make it easier for the algorithms to perform the analysis. We need adaptive solutions that do not require frequent human intervention for calibration and setup. Furthermore, the numbers of false alarms must be limited and, at the same time, the number of anomalies and true alarms that are not detected must be zero. The main objective is the monitoring of different types of activities and conditions. Specifically:

General behaviors examples are: how often do they use the bathroom, how often do they go to the fridge, how often do they sit down.

Medical conditions examples are: heart monitoring, breath rate, temperature, weight, SPO2

Adherence to prescribed plans examples are: are they practicing exercises and/or specific activities, are they taking medications in the appropriate time intervals

Other personal data examples are: quality of sleep, movements, gait, activities of daily living

1.3 Contribution

In this project, I propose a paradigm shift in assistance, in which intelligent environments act as personalized, social-aware and evolving cognitive prostheses to assisted people, which adaptively integrate their cognitive capabilities. The target population are the elderly and people with mild cognitive impairments, partially autonomous, but in need of a light assistance, possibly in a post-hospitalization stage. The project aims to design and implement a model of protected discharge, in which the patient, after being discharged from the hospital, is hosted for few days (about one week) in an apartment. The facility is located within the Galliera Hospital in Genova (Italy) and it is equipped as a comfortable apartment, where patients can be monitored by a system of sensors, while physicians and nurses have the possibility of monitoring them remotely. The system consists of a set of subsystems, each one developed to solve specific problems. Each part concurs to the core task, the estimation of the *frailty index* of the patient, providing integrated statistical tools to quantify motility, daily living activities and, in general, quality of life. I intend to quantitatively evaluate the frailty of the elderly considering the physical and cognitive dimension. In particular, I used visual computing tools to analyze patients' motility and postural transfers, based on which I formulated a Motility Index (MI) to compare patients' performances. I performed this evaluation considering short time windows (up to few days), providing a significant advance with respect to the current literature usually based on long observations of the patient (6-12 month) (see e.g. (Scanail et al., 2006)). Moreover, I assessed the cognitive status of patients, using a game-like approach based on virtual reality (VR) tools, that represent an alternative to traditional tests in which patients can be evaluated in ecological conditions (Spooner and Pachan, 2006). In fact, VR allows to reproduce complex situations of daily living, where psychopathological reactions and cognitive functions of patients

can be more reliably evaluated.

The realization of the prototype is structured in three phases and I made contributions to each of them.

The first phase is a survey of the current situation in order to identify and numerically quantify the eligible hospital population. During this phase I collaborated with doctors and management engineers from the hospital in order to identify hospital costs and the time gap between the moment in which a patient is considered clinically dischargeable and the moment when he/she is actually discharged. The objective of this phase is to elucidate the number and types of patients subject to this gap and collect information about them, including age, anamnesis, date of potential dischargeability and date of actual discharge. We defined the characteristics of the patients that best fit with our idea and how long these patients would have to stay in the facility to obtain benefits both for a reduction of hospital costs and for the improvement of their health. All these considerations have been done taking into account safety and security rules.

The second phase consists on the definition of the biological parameters to be monitored and the technological devices needed. For this purpose, I collaborated with doctors and nurses to identify a set of vital parameter to be monitored and the devices present on the market. We chose sensors that were easy to use for elderly patients and that cover and complement the measures that doctors usually perform on this kind of patients. I also evaluated all the ambient and wearable technology for our necessity. These technologies had to be blended into the environment, so that the patient does not have the feeling of being oppressively controlled.

The goal of the last phase is the definition of the ideal architectural characteristics of the semi-hospital residence. For this task I worked with the architects that contributed to the realization of the project. The aim of this phase was to identify architectural and technological design solutions to facilitate the recovery of inpatients before their discharge from hospital. Starting from the identification of the users needs, I participated in the definition of solutions and products that integrate the architectural environment with the monitoring system, ensuring maximum safety, comfort and usability.

Once the prototype was realized, I participated in the implementation and test of methods to automatically analyze patients' motility through the use of the sensors installed in the facility. I also trained doctors and nurses to the use of all the

technologies available inside the apartment and then we started with the volunteers enrollment. I started with some young volunteers to train the system and then I enrolled healthy elderly volunteers to test the performance of my monitoring system. During this phase, I collected and analyzed data using advanced statistical tools. I also trained volunteers, especially the elderly. I interacted with doctors to learn the medical analysis they performed on patients and to compare their qualitative results with my automatic and quantitative data analysis. We planned meeting sessions with doctors to solve open problems and to improve the obtained result.

During my PhD I published some conference papers ([Patrone et al., 2018](#)), ([Martini et al., 2018b](#)), book chapters ([Chessa et al., 2017](#)), ([Martini et al., 2018c](#)), and journal paper ([Martini et al., 2018a](#)) (see Section 6.4). I also had the opportunity to perform some oral and poster presentations (see Section 6.5). Because of the multidisciplinary content of my project, I presented my work to a very diverse community: doctors, computer scientists, engineers, and architects.

1.4 Outline

This thesis is structured as follows: in Chapter 2, I will explore the concept of frailty, its importance in the assessment of the overall well-being of elderly patients, and their risk of mortality. I will explore available methods to evaluate patients' frailty and new strategies allowed by the advent of technologies, showing the advantage and potential of its continuous automatic assessment and the open challenges of these approaches. Finally, I will summarize the research present in the state of the art in this field, with a particular focus on smart homes.

Chapter 3 is focused on the description of the model of protected discharge we designed and implemented in order to perform a continuous and automatic evaluation of frailty of elderly patients. I will describe the apartment and the devices installed to perform my analysis.

Chapter 4 is a technical part in which I will describe the methodology of my approach. I will explain how I used technology to evaluate the motility of the elderly. Starting from the description of the monitoring system, the motility quantities estimation and the formulation of a Motility Index, used to complement and enrich the qualitative analysis performed by physicians.

Chapter 5 shows the experiments I performed. It starts from the enrollment of volunteers, going on with the analysis I performed and the relative problems I

encountered. In that chapter, I will show the results I obtained, their potential and limitations.

This dissertation is concluded by Chapter 6, where I summarize the most relevant results I obtained, giving suggestions for future implementations.

Chapter 2

State of the art

This chapter starts from observations on the aging population and the consequent importance of the assessment of the frailty of elderly, how this is calculated in geriatrics, highlighting the advantages that can be brought by its continuous assessment. In the course of the chapter, I also underlined the problem of prolonged hospitalization of the elderly and how this causes a worsening of patients' health and an increase in hospital costs. Current trends are the creation of smart homes that, thanks to technological developments, allow to solve the problem of delayed hospital discharge, maintaining and even improving the necessary health and safety requirements.

The chapter is organized as follow, from Section 2.1 to 2.6, I will illustrate the state of the art on the field. In Section 2.7, I identify a set of challenges for continuous automatic assessment.

2.1 Introduction

The human being is a complex organism, whose well-being may be described following several dimensions, encompassing the physical, cognitive, psychological, economic, and social domains. The process of aging typically reduces the individual's potential in one or more of these domains, leading to a condition of vulnerability and clinical instability. The changes that constitute and influence aging are complex. At a biological level, aging is characterized by a gradual, lifelong accumulation of molecular and cellular damage that results in a progressive, generalized impairment in many body functions, an increased vulnerability to environmental challenges and

a growing risk of diseases and death (Kirkwood, 2008). This is accompanied by a broad range of psychosocial changes.

As people age, they are more likely to experience multi-morbidity that is, the presence of multiple chronic conditions at the same time. This can lead to interactions among conditions. As a result, the impact of multi-morbidity on functioning, quality of life and the risk of mortality may be significantly greater than the sum of the individual effects that might be expected from these conditions. Predictably, multi-morbidity is also associated with higher rates of health-care utilization and costs.

To highlight this condition, in the last decade, the medical literature has introduced the definition of *frail elderly*, a fragile individual with an elevated risk of complications, that may result in loss of functional autonomy and in a high risk for adverse health outcomes, including hospitalization, institutionalization, and mortality (Fried et al., 2004). It is generally agreed that frailty is a state of high vulnerability for adverse health outcomes, including disability, dependency, falls, need for long-term care, and mortality. The challenges in finding a standard definition of frailty that could be widely recognized and valid in different settings makes any estimation of its prevalence approximate and tentative.

Frailty is defined in the literature as a parameter formed by all the following measures:

- Functional: that is the capability of the person to perform Activity of Daily Living (ADL) or Instrumental Activity of Daily Living (IADL)
- Cognitive: that is reaction to stimuli and answer to questionnaires
- Motility: that is velocity of walk and fall risk
- Medication adherence
- Nutrition

Starting from this definition of frailty, geriatricians focus their attention on the following frailty measures:

- Unintentional weight loss
- Exhaustion

- Slow gait speed
- Low physical activity
- decrease grip strength

As pointed out by [Pilotto et al. \(2008\)](#), a careful evaluation of the frailty is important to assess the overall well-being of the patient, to estimate the likelihood of functional loss, and to predict the mortality risk. This evaluation is particularly important during hospital stay, since it is well known that hospitalization, especially if extended, may lead to new disabilities and may drastically deteriorate the risk of associated mortality ([Volpato et al., 2016, 2007](#)). In fact, besides the disabling effect of the acute event, hospitalization itself might represent an additional stressor in terms of environmental hazards, reduced caloric intake, low physical activity or prolonged bed-rest, depressed mood, and social isolation. The decline in functional status during hospitalization has important consequences in terms of quality of life and health care utilization, as it has been associated with the risk of longer hospital stay, home care placement, and mortality. Over the years, geriatricians developed different protocols to evaluate frailty. These protocols are characterized by the same goal, but lacking a universally accepted standard, they follow different strategies ([De Vries et al., 2011](#)). Some of them are unidimensional, as they focus on one specific domain (either cognitive or physical) others are multi-dimensional and take into account different domains, as discussed in ([Roppolo et al., 2015](#)). In any case, all of them are sporadic, subjective, and can not be performed by a non-expert physician. Last but not least, they suffer from bias due to the possible effect of a patient's anxiety towards medical tests and questionnaires. Recently, with the advent of new assistive technologies, various approaches to the automatic analysis of a patient's health status and behavior have been proposed ([Gianaria et al., 2016](#)). In Chapter 3, I will show the results of my research carried out in the field, with a special reference to methods for automatically estimating gait, behavior, motility, or activities of daily living. A core aspect of automatic methods is their objectivity, and the fact that they allow for a better, or complementary analysis of human behaviors. Moreover, automatic systems also have the potential for a continuous analysis of the patient, or at least for an assessment covering longer periods of time, which would improve the statistical significance of the outcomes ([Cao et al., 2009](#); [Zouba et al., 2010](#)). As a further potential application, such automatic analysis could be carried out in home environments, where the patient feels more comfortable, inducing a

lower behavioral bias. These aspects will be discussed with the aim of identifying a longer term perspective of the current research.

2.2 How frailty is evaluated by geriatricians

Frailty is considered to be highly prevalent with increasing age and to confer high risk for adverse health outcomes, including mortality, institutionalization, falls, and hospitalization. Potential definitions of frailty abound, defining frailty as synonymous with disability, co-morbidity, or advanced old age. Increasingly, geriatricians define frailty as a biologic syndrome of decreased reserve and resistance to stressor, resulting from cumulative declines across multiple physiologic systems, and causing vulnerability to adverse outcomes.

An accurate estimation of frailty of an elderly person is an important objective to assess the overall patient well-being and to predict the risk of mortality ([Angleman et al., 2015](#); [Pilotto et al., 2008](#)). Moreover, a correct quantification of frailty is particularly useful in elderly patients after a prolonged hospital stay, as it can lead to the development of new disabilities and dramatically worsen the risk of mortality, as pointed out by ([Volpato et al., 2016](#)) (see also ([Volpato et al., 2007](#))). While it is common knowledge that an accurate estimation and follow-up of frailty is essential for assisting geriatric patients, a universally shared definition of how to evaluate it has not yet been reached. Over 20 very heterogeneous indices have been introduced in the literature ([De Vries et al., 2011](#)). As discussed in ([Azzopardi et al., 2016](#)) and in ([Rockwood et al., 2015](#)), most state-of-the-art tools to evaluate frailty are not homogeneous: many are simply dichotomous, other are more exhaustive and consider different aspects of the overall health status of a patient. We mention the Functional Domains tool ([Strawbridge et al., 1998](#)), the Frail Elderly Functional Assessment Questionnaire ([Gloth III et al., 1999](#)), and the Groningen Frailty Indicator ([Schuurmans et al., 2004](#)).

More recently, new multi-dimensional strategies were proposed, such as the Multi-dimensional Prognostic Index (MPI) scores ([Pilotto et al., 2008](#)). All these variants have some limitations, such as the lack of objective unbiased measures based on performance tests. This lack of systematization makes frailty indices difficult to use in the clinical practice. Current scores are based on episodic evaluations of several dimensions: clinical, cognitive, functional, nutritional and social and multi-morbidity defined according to the International Classification of Functioning, Disability, and

Health¹. Motility deficits are assessed by medical staff through sporadic quantitative tests, such as the evaluation of:

- hand grip: the test is performed with both hands using a hand-held calibrated dynamometer, the subject is asked to squeeze the hand as hard as possible for few seconds.
- Time Up and Go (TUG) test: starting sitting correctly in a chair with arm resting, the subject is asked to stand up, walk for 3 meters, turn around and walk back to the chair and sit down again (see Appendix B).
- four meters walk test: the test consist in record the time that it takes the subject to walk four meters.

The other dimensions are normally assessed through qualitative evaluations and patient's self-reported questionnaires. The latter are being used more frequently in epidemiological studies, health service research, and in clinical trials to evaluate therapeutic interventions because they can capture the self-perception of the disease (Gobbens et al., 2010; Mulasso et al., 2016). It is clear how defining a score based on quantitative and frequent observations over an extended period of time would improve the assessment of frailty and, possibly, provide a more reproducible and stable measure over time.

2.2.1 The Comprehensive Geriatric Assessment (CGA)

Since mortality in older subjects results from a combination of biological, functional, psychological, pathological, and environmental factors, tools that effectively identify patients with low life expectancy should take a multidimensional approach. The Comprehensive Geriatric Assessment (CGA) is a multidimensional, diagnostic process intended to determine an elderly person's medical, psychosocial, and functional capabilities, and problems with the objective of developing an overall plan for treatment and short- and long-term follow-up (Brown et al., 1988). Comprehensive assessment methodologies are believed to be particularly suited for evaluating older people that suffer from multiple illnesses and significant disabilities. Since in older subjects the occurrence of negative outcomes, such as institutionalization, hospitalization, or mortality, results from a combination of biological, functional,

¹<http://apps.who.int/classifications/icfbrowser/>

psychological, pathological and environmental factors, tools that effectively identify older high-risk patients should take a multidimensional approach. A typical assessment schedule of CGA includes a number of evaluations that focus on clinical and functional areas to establish individual impairments or risk factors. Widely diffuse in the geriatric practice, these instruments proved to be clinically useful for evaluating functional disabilities in Activities of Daily Living (ADL) (Katz et al., 1970) and the Instrumental Activities of Daily Living (IADL) (Lawton MP, 1969), the cognitive status for dementia screening (by the Mini Mental State Examination, MMSE (Folstein et al., 1975) or the Short-Portable Mental Status Questionnaire, SPMSQ (Pfeiffer, 1975)), the risk or the presence of depression (by the Geriatric Depression Scale, GDS (Hoyl et al., 1999)), the nutritional status (by the MiniNutritional Assessment, MNA (Guigoz and Vellas, 1999)) or the risk of pressure sores (Bliss et al., 1966) in patients at high risk of immobilization or bed-ridden (by the Exton-Smith scale, ESS). Moreover, the CGA includes a careful evaluation of comorbidities by Comorbidity Illness Rating Scale, CIRS (Linn et al., 1968), or other tools (Bari et al., 2006), as well as of medication use for the evaluation of the appropriateness of prescriptions (Lau et al., 2005) and the risk for adverse drug reactions (Franceschi et al., 2008).

2.2.2 The Multidimensional Prognostic Index (MPI)

For patients and caregivers, prognostic information is needed to make decisions concerning clinical management, discharge plan, and follow-up. Starting from the standardized Comprehensive Geriatric Assessment (CGA), a Multidimensional Prognostic Index (MPI) for 1-year mortality has been developed. The MPI is a derived index based on six commonly used geriatric assessment scales exploring the cognitive, functional, nutritional and clinical status, as well as on information about drugs taken and a patient's social support (Pilotto et al., 2008). Its long-term predictive value has been established in the overall hospitalized population (Pilotto et al., 2012) as well as in older subjects hospitalized for specific clinical conditions. The MPI has been found to be predictive of in-hospital length of stay and of hospital admission in an outpatient setting (Volpato et al., 2014). The MPI is calculated by aggregating data from specific questionnaires, detailed below (Pilotto et al., 2008). The MPI includes 63 items distributed in 8 domains of CGA as follows:

ADL Activities of Daily Living defines the level of dependence/independence of 6 daily personal care activities including bathing, toileting, feeding, dressing,

urine and bowel continence and transferring (in and out of bed or chair). For each item there is a score that corresponds to the number of ADLs preserved.

IADL Instrumental Activities of Daily Living assesses independence in 8 activities that are more cognitively and physically demanding than ADL, including managing finances, taking medications, using the telephone, shopping, using transportation, preparing meals and doing housework. As with the ADLs score, physicians evaluate the number of capabilities preserved.

SPMSQ Short Portable Mental Status Questionnaire is a 10-item questionnaire that assesses orientation, memory, attention, calculation and language. Doctors count the number of errors made by the patients answering the questions.

MNA Mini Nutritional Assessment is composed of 18 items and includes information on anthropometric measures, lifestyle, medication and mobility, number of meals, food and fluid intake, autonomy of feeding, and self-perception of health and nutrition.

ESS Exton-Smith Scale is used to evaluate the risk of developing pressure sores. This 5-item questionnaire determines physical condition, mental condition, activity, mobility and incontinence. For each item, a score from 1 to 4 is assigned.

CIRS-CI Cumulative Index Rating Scale uses 5-point ordinal scales (score 1–5) to estimate the severity of pathology in each of 14 systems, including cardiac, vascular, respiratory, eye-ear-nose-throat, upper and lower gastroenterological diseases, hepatic, renal, genitourinary, musculoskeletal, skin disorders, nervous system, endocrine-metabolic and psychiatric behavioral problems.

Number of drugs A score from 0 to 1 is assigned counting the number of drugs the patient take, i.e. from 0 to 3 the score is 0, from 4 to six the score is 0.5 and above 7 the score is 1

Cohabitat status A score from 0 to 1 is assigned if the patient lives with family (0), institutionalized (0.5), or alone (1).

See appendix [A](#) for a more detailed explanation.

For each domain a tripartite hierarchy is used, i.e. 0 = no problems, 0.5 = minor problems, and 1 = major problems, based on conventional cut-off points derived

from the literature for the SPMSQ, MNA, ESS and ADL/IADL or by observing the frequency distribution of the patients at various levels to identify points of separation for comorbidities and number of medications. The sum of the calculated score from the eight domains is divided by 8 to obtain a final MPI score between 0 and 1. For analytical purposes, the absolute values of MPI are not considered and physicians express MPI as low (MPI value ≤ 0.33), moderate (MPI value between 0.34 and 0.66) and severe risk (MPI > 0.66) of mortality (Pilotto et al., 2007).

2.3 Advantage and potential of continuous automatic assessment

Recently, with the advent of assistive technologies and more effective data analysis tools, various approaches have been proposed that could be effectively used to provide an automatic assessment of frailty. Most of these approaches would also allow for a less sporadic and more objective evaluation. Electronic sensors, video-monitoring, remote health monitoring and equipments such as fall detectors, door monitors, bed alerts, pressure mats and smoke and heat alarms can improve patients' safety, security and ability to cope at home.

In this section, I summarize relevant research works highlighting their potential benefit to the frailty index estimation. A first line of research explored the possibility of providing physicians with automatic analysis tools to adopt in their daily practice. The work of Greene et al. (2013) compares the performances in manually classifying frail or non-frail by means of the TUG (Time Up and Go) test and grip strength, with an automatic classification based on a regressor analyzing inertial sensor data acquired during TUG. This test is a standard motility assessment, the time taken to complete the test has been shown to be a strong predictor of frailty and is commonly used for assessing risk of falls in older adults. The results show the benefits of adopting an automatic analysis. Gianaria et al. (2016) propose a prototype of a frailty detection tool based on the analysis of video sequences acquired through passive depth sensors (Kinect) during the TUG test. The authors developed computational vision techniques to analyze the patient's gait and infer information on motility. An automatic analysis of frailty, based on routine visits combined with the digital health record (DHR), was recently proposed by Clegg et al. (2016).

The benefit of an automatic system is that it would provide alternative or additional information to the geriatrician, and it could be used by the non-specialist/general practitioner for a less sporadic assessment on frailty.

A second line of research are the so-called smart environments that would allow to monitor patients at home. [Cao et al. \(2009\)](#) present a context-aware system based on video analysis and a reasoning mechanism; [Zouba et al. \(2010\)](#) describe the prototype of a smart home equipped with cameras and environmental sensors, [Bathrinarayanan et al. \(2013\)](#) evaluate an event recognition system based on video analysis. In all cases, the main effort is in recognizing actions and instrumented activities. They primarily focus on the functional domain, trying to detect anomalies with the goal of raising alarms. A more in-depth analysis of the state of the art concerning smart homes can be found in Section 2.5.

The benefit of smart environments is that they may produce an up-to-date continuous analysis of the patient's status, in a less stressful context. Moreover, the very large amount of data they gather may be the source for a more complex multi-dimensional analysis of the patient's habits and behaviors.

To summarize, automatic systems may participate in the health status assessment at different levels. Indeed, we may consider

- *A continuous assessment of the patient at home*, whose outcome is more robust as it relies on a longer term analysis, but it is harder to accept by the patient and the family and it is more complex to implement.
- *An automatic but not continuous analysis at the doctor's office* which may add an objective or complementary view, but it might be influenced by anxiety towards medical tests.
- *A short-term continuous assessment during hospital stay*, that could be seen as a trade-off between pros and cons from the above alternatives, but has the limitation of analyzing the patient in a not so comfortable setting where staying in bed is encouraged or needed.
- *A short-term continuous assessment in an ad hoc home-like hospital facility* to be used for a short time (with a maximum of 3 or 4 days) where the patient is free to move and carry out common daily activities, and in the meantime the system analyses the patient considering multiple dimensions.

The latter is the possibility that appears to have a higher benefit in the overall evaluation of the patients, at the cost of an initial investment in designing an ad hoc environment. Taking into account these considerations, the idea of a model of protected discharge was born. A detailed explanation of the facility is presented in Chapter 3 and the results I obtained are shown in Chapter 5 with a special overview of the problems I found during the data acquisitions and patients enrollment.

2.4 Ambient Assisted Living

In order to decrease the costs of healthcare and improve the quality of patient life, many fields of research including engineering, medicine, economics and psychology are working together to develop assistive technologies that improve the quality of life. Any technology that has an impact on the psycho-physical well-being of the individual can be identified as a technology that improves the quality of the subject's life. However, giving a definition of quality and well-being is not objectively simple because it depends on a multidimensional evaluation of various aspects that may be part of our existence (Schulz et al., 2012). When technology for the improvement of the quality of life is addressed to people with special needs, we need an intelligent system or intelligent living environments that improve the cognitive and motor functions of older people with disabilities, increasing their self-esteem (Kanade, 2012). Ambient Assisted Living (AAL) includes all those technologies that realize this intelligent system in a smart environment. AAL includes numerous emerging fields like:

- assistive domotic
- tele-medicine
- assistive robotic
- human machine interface
- human machine interaction
- tele-rehabilitation
- wearable devices
- textronics

- personalized medicine

The objectives of AAL systems are:

- increase the security and autonomy of the individual by preventing social isolation and building a social network around it;
- support the maintenance of health and functional abilities of the elderly;
- promote a better and healthy lifestyle for individuals at risk;
- support and train caregivers and family members, in increasing the use of these resources and technologies;
- reduce national health costs.

In order to meet these macro objectives, the technologies present in a smart living environment must be:

- inter-operable: integrate solutions and commercial components into an easy-to-use system
- smart: interpret data acquired by the sensors in information for the individual
- non-invasive: they must increase and not reduce the quality of life of the subject.

In this scenario, problems that lead to the lack of large-scale diffusion of these systems derive from the difficult adaptation of these technologies to the lifestyle and habits of the subject, and lack of simple usability and acceptability. There are also problems related with security concerns such as privacy, data integrity, and reliability of sensors. Within an AAL system, the improvement of human-machine interaction is one of the fundamental aspects in order to obtain an intelligent living environment that can interact in a natural and intuitive way with the individual. In this particular area of research there is therefore the need to know emotions and the cognitive reactions of individuals, eliminating the gap between machine and human being.

Analysis of elderly needs According to Maslow's theory (Maslow, 1943), human needs can be classified into a hierarchical model. When this model is applied to the needs of the elderly, we can highlight five areas that contribute to their quality of life. The common health care is based on the longevity of life that is not the only goal for the well-being of the elderly, since today it must be coupled with a high quality of life. An adequate amount of awareness on particular needs of the elderly can have a direct impact on their health and well-being. Moreover, the knowledge of the needs of the elderly can help not only them but also the family and health workers to achieve the highest level of satisfaction, self-esteem and self-realization.

From Maslow's (Maslow, 1943) hierarchical model, the particular needs of the elderly could be summarized as follows:

- *Physiological needs* all people have physiological needs, regardless of their age. Food, drink, sleep and the treatment of diseases are fundamental tasks for survival.
- *Safety* once physical survival is safeguarded, attention must be paid to security. This is especially true for seniors who usually have to stay at home alone and for a long time.
- *Social needs* all humans are, by nature, rational and social and they do not like to feel isolated or cut off from society. Because of health problems or the impossibility of being able to leave the domestic environment, aging often reduces social opportunities, and most of the elderly spend their time in solitude. Social needs include all the opportunities that can involve the elderly in social events with family, friends and the community.
- *Need of self-esteem* the elderly, like all people, want to feel recognized and appreciated for their ideas, skills and abilities. In particular, they need to do something or to be considered useful. Aging often reduces awareness due to illness, disability and fragility.
- *Need of self-realization* self-realization is a state reached by relatively few people. This important feature can be represented by all those people who tend to focus on the reality of life, who are problem solvers and also have the point of view that the path they undertake during their life is just as important as their final destination. With all the experience of their life and their maturity, seniors

should be the first candidates to achieve self-fulfillment. However, the aging process often diminishes this self-fulfillment level together with self-esteem and social connection, leaving elderly population in the lower survival levels.

The AAL systems have a great potential to compensate all age-related dysfunctions and impairments. Emerging technologies in assistive living environments present a considerable opportunity to improve the quality of life of many elderly by providing greater confidence and security, while at the same time supporting mobility, independent living, and social participation.

2.5 Smart homes

In an aging world, maintaining good health and independence for as long as possible is essential. Instead of hospitalization or institutionalization, the elderly and disabled can be assisted in their own environment 24 hour a day with numerous smart devices. The concept of smart home is a promising and cost-effective way of incorporating Ambient Assisted Living, improving home care for the elderly and the disabled in a non-obtrusive way, allowing greater independence, maintaining good health and preventing social isolation ([Chan et al., 2009](#)). The term smart home is used for a residence equipped with technology that allows the monitoring of its inhabitants and/or encourages independence and the maintenance of good health. Smart homes are purposely designed living spaces that provide interactive technologies and unobtrusive support systems to enable people to improve their levels of independence, activity, participation or well-being ([Adair et al., 2013](#)). The challenge with smart-home technologies is to create a home environment that is safe and secure to reduce falls, disability, limitations, stress, fear, or social isolation ([Barlow and Venables, 2004](#)). They usually aim to perform functions without disturbing the user and without causing any pain, inconvenience, or movement restrictions. Smart homes contribute to the support of the elderly, people with chronic illness, and disabled people living alone at home. This new mode of health assessment can improve the quality and variety of information transmitted to the clinician. Measures of physiological signs and behavioral patterns can be translated into accurate predictors of health risk, even at an early stage, and can be combined with alarm-triggering systems as a technical platform to initiate appropriate action. Telecare can provide the infrastructure for coordinating multidisciplinary care outside the hospital.

Different smart homes may exploit different types of sensors, depending on the specific requirements. Assistive environments may include bed sensors to detect patient heart rate, respiration and restlessness, motion sensors to detect motion within the home or apartment, devices that provide data regarding patients' location over time, kitchen safety sensors used in combination with motion sensors to detect activities of daily living and to generate alarms, falls detection sensors for passive monitoring of patients falls, cameras and RGB-D sensors for activity detection, and motion and activity analysis.

Most smart home technologies passively collect and share elderly well-being information with the family members and primary care providers. These devices collect multiple types of data, including physiological, location or movement data. Algorithms transform the raw data into activity patterns, which can be used for early detection and intervention by healthcare providers or families (Courtney et al., 2008).

Closely related to the concept of smart homes are techniques to address human activity detection. Most works in this area use the concept of "activity" as a building block for health monitoring and assisted living. The process of identifying a specific activity encompasses the selection of the appropriate set of sensors, the correct preprocessing of their provided raw data, and the learning/reasoning using this information (Giannakouris, 2008).

There are several studies on smart home for the elderly, and various different models have been developed. Each of the models differs from one another by the types and arrangements of the installed devices, Table 2.1 shows some examples.

Table 2.1 Assistive Smart Home Projects

Project	Objective	Reference
Aging In Place	Long-term care model for seniors in terms of supportive health	Rantz et al. (2011)
At Home Despite the Age	Model for senior housing that consist of a dwelling which fosters an active and independent life style despite the age using smart technologies	http://mimowieku.pl/

Aware Home	Smart home based on ubiquitous computing that senses and recognizes potential crises, to assist declining elderly memory and find behavioral trends	Kientz et al. (2008)
CareLab	Monitoring and assistance component including a hybrid reasoner that is able to adapt planned and running treatments according to the current situation and context	Nick and Becker (2007)
CASAS	Noninvasive assistive environment for dementia patients at home	Rashidi and Cook (2009)
DOMUS	Smart home designed to observe users' activities interacting with the ambient intelligence of the environment	Bouchard et al. (2007)
Elite Care	System for unobtrusive detection of movement in bed that uses load cells installed at the corners of a bed	Adami et al. (2010)
ENABLE	Promotes the well-being of people with early dementia with several features such as a locator for lost objects, a temperature monitor and an automatic bedroom light	Van Berlo (1998)
Gator Tech	Assistive environments such as homes mappings between the physical world and remote monitoring and intervention services	Helal et al. (2005)
HIS	Diagnostic system based on monitoring human activity rhythms	LeBellego et al. (2006)
ICT4LIFE	Real-time monitoring of patients, with the aim of preventing fall risk, social isolation, and to promote patients independence	http://www.ict4life.eu
MavHome	Technologies to Manage Adaptive Versatile environments	Youngblood et al. (2005)

Millenium Home	Multimodal interface to a pervasive/ubiquitous computing system that supports independent living by older people in their own homes	Perry et al. (2004)
ProSAFE	Support automatic recognition of resident activity and falls utilizing a set of infrared motion sensors	Chan et al. (2005)
SELF	System that observes the person's behavior with distributed sensors invisibly embedded in the daily environment, extracts physiological parameters from it, analyses the parameters, and accumulates the results, used for reporting useful information to maintain the person's health	Nishida et al. (2000)
Sweet Home	Provide audio-based interaction technology that allows the user to have full control over their home environment, detect distress situations and ease the social inclusion of the elderly and frail population	Vacher et al. (2011)
Usefil	Unobtrusive sensor network, such as a Wrist Wearable Unit, a camera strategically placed behind a mirror, coupled with a microphone and a Kinect sensor provides in-home monitoring	https://www.usefil.eu/
WTH	Automated monitoring system for home health care based on automated electrocardiogram (ECG) measurements taken while in bed, in the bathtub, and on the toilet	Tamura et al. (2007)
Dementia home	A show home designed around concepts and technologies which will allow people with dementia to live independently for longer	https://bit.ly/2xvhPyJ

SMARTA	Home telemonitoring of vital parameters and detection of anomalies in daily activities, thus supporting active aging through remote healthcare	Pigini et al. (2017)
HOPE	Integrated, smart platform that enables the elderly people with Alzheimer's disease to use innovative technology for a more independent life	http://www.hope-project.eu
NESH	Non-intrusive Elderly Smart Home (NESH) will equip the elderly peoples homes with a set of sensors that will monitor them non-intrusively	https://bit.ly/2D1NvO2

A common denominator of all these solutions is the fact that they leverage the availability of long term observations of the monitored environment.

In the literature, there are several studies that investigate the problem of daily activity recognition from data fusion of heterogeneous sensors. Elderly daily activities monitoring is addressed in (Cao et al., 2009), where the authors have proposed a description-based approach in which the human body context (e.g., sitting, standing, walking) is provided from a set of cameras, while the environmental context is obtained from accelerometers attached to objects of daily living. A rule-based reasoning engine is used for processing and combining both context types. Similarly, in (Zouba et al., 2010) the authors have evaluated a video monitoring system for the identification of activities of daily living of older people on a model apartment with home appliances, equipped with pressure and contact sensors. People movements and posture are tracked over time by using RGB-D cameras. Multi-sensor environments, in particular the ones with heterogeneous sensors, open the need to investigate robust data fusion techniques: for example, in (Gao et al., 2012) the authors have demonstrated the fusion of data from inertial sensors worn at the waist, chest, thigh, and side of a person body for activity recognition. They propose a multi-sensor fusion framework, which consists of a sensor selection module and a hierarchical classifier. Also other approaches (e.g. see (Liu and Liu, 2010)) have used classifiers for inertial sensors fusion on activity recognition, though such approaches present some disadvantages, e.g. the presence of motion noise, and the need of inter sensor calibration.

Vision-based approaches In the reminder of this section, we focus on vision-based approaches, leveraging the use of RGB or RGB-D data streams, similar to my approach (I will discuss in Chapter 4). The use of vision sensors gives rise to privacy issues as well as considerations on the level of acceptance and perception of elderly patients (Adair et al., 2013). Smart technologies appear to be accepted by older adults, their family members, healthcare professionals, and care givers. Nevertheless, older adults' perception of privacy can inhibit the acceptance and subsequent adoption of cameras (Courtney, 2008). For this reason, it is necessary to adopt vision sensors that minimize the intrusion into patient's life, e.g. to use only depth sensors in bedrooms, and to perform the processing online, without the need of storing any image data.

As previously mentioned, in (Zouba et al., 2008) the authors present a cognitive vision approach to recognize a set of interesting ADLs for the elderly at home. This approach is composed of a video analysis component and an activity recognition component. A video analysis component includes person detection, person tracking, and human posture recognition. The activity recognition component contains a set of video event models and a dedicated video event recognition algorithm. In the study, the authors collaborate with medical experts (gerontologists from Nice hospital) to define and model a set of scenarios related to interesting activities of the elderly. Some of these activities require to detect a fine description of human body such as postures. For this purpose, they propose ten 3D key human postures useful to recognize a set of interesting human activities regardless of the environment.

Among the tools available in the Computer Vision field, of particular interest for application in the assistive living domain is human posture recognition. Human posture can be determined and classified by considering several explicit or statistical models, in 2D or 3D workspaces. In Joumier et al. (2011), the authors propose an automatic video monitoring system, which takes as input video streams on which they perform detection, classification, and tracking processes, and a priori knowledge for 3D scene modeling and recognition of events. They extract attributes (e.g., duration, walking speed) of automatically recognized physical task events in order to identify differences between Alzheimer and healthy participants groups. A fall detection system, to be employed in a prototype University hospital in Minnesota, is proposed in Banerjee et al. (2012), where they use features extracted from three dimensional point clouds created from Kinect depth images. It is worth noting that the choice of relying uniquely on depth images is due to privacy reasons. Finally,

in Bathrinarayanan et al. (2013), a video monitoring system for event recognition of older people using a hierarchical description-based approach and a RGB camera as input is presented. The authors addressed the issues of recognizing both physical tasks and Instrumental Activities of Daily Living, during a clinical protocol for an Alzheimer disease study.

2.6 Technologies currently on the market

With the phenomenon of aging in place becoming more popular for the elderly. We find that there are things that can be done to assist them through the use of smart home technology. Smart Home technology aims to tackle the struggles that you might face staying in the home long term.¹

Many smart homes today adopt the concept of ubiquitous sensing where a network of sensors integrated with a network of processing devices yield a rich multi-modal stream of data. These sensory data are analyzed to recognize and monitor Basic and Instrumental Activities of Daily Living performed by the residents such as bathing, dressing, preparing a meal, and taking medication (?). This approach has the potential to allow smart homes to capture patterns possibly reflecting physical and cognitive health conditions and then recognize when the patterns begin to deviate from individualized norms and when atypical behavior may indicate problems or require intervention (Ding et al., 2011). Technology can provide continuous assessment of the health and cognitive status of the patient, contribute to his or her independent living, prevent dangerous situation such as fall risk, and detect anomalies in the patient behavior.

Although the use of smart home technologies has an array of potential benefits in improving quality of life for elderly persons, a successful promotion of smart home technologies would require an essential assessment of the needs, concerns, psychological accessibilities, and the perceptions. Some of the concerns that must be investigated before adapting smart home technology include: customizing systems to meet the needs of related stakeholders i.e. elderly persons, caregivers, and elderly families; making systems user friendly; and costs optimizing of modifying existing home to accommodate the assistive technology (Visutsak and Daoudi, 2017).

¹<https://diysmarthomeguide.com/complete-guide-smart-home-technology-elderly/>

Ambient sensors The ambient sensors that are used for elderly care can be placed in different locations in a smart home to monitor human behavior or health status (Uddin et al., 2018). Ambient Assistive Living (AAL) technologies are embedded (distributed throughout the environment or directly integrated into appliances or furniture), personalized (tailored to the users' needs), adaptive (responsive to the user and the user's environment) and anticipatory (anticipating users' desires as far as possible) (Patel et al., 2012). Ambient sensors can monitor activity patterns, sleep quality, bathroom visits etc., and provide alerts to caregivers when abnormal patterns are observed. Environmental sensing is commonly based upon many simple binary sensors throughout the home, video cameras, and RFID technology.

Binary sensors One particular type of sensor that is commonly used in smart homes are binary sensors, which simply detect the state of an object or movement with a single digit '1' or '0'. Various types of binary sensors have been used in smart homes including motion detectors, pressure sensors, and contact switches. Motion detectors and pressure sensors are usually used to detect the occupant's presence and location throughout the house.

Video cameras are considered high-content sensors which provide rich sources of information both for human observation and for computer interpretation. However, they usually introduce more technical challenges with respect to storage requirements and information extraction, as well as social challenges around privacy when compared with simple binary sensors. Cameras are installed on the walls or ceilings to detect activity through background subtraction, body shape extraction, feature analysis, and machine learning. Among many applications, video monitoring technology has mostly been used to detect activities of daily living and falls or other significant events (Uddin et al., 2018).

Radio frequency identification (RFID) is a technology that uses communication via radio waves to exchange data between a reader and an electronic tag. When interrogated by a RFID reader, the tags respond with a unique identifier as well as information stored in their memory.

Ambient intelligence technologies are also useful to augment a typical hospital room with smart features that assist both patients and medical staff. An example scenario consist of an application for a touch pad that helps the patient to use the hospital facilities (light, blinds, rear TV, nurse calls in case of emergency or any other specific reason). The application can also provides a scheduling mechanism that assists the patient in organizing important activities and needs such as taking

pills. In the case of the medical staff, the application aims to facilitate the visit to the patient, as well as the analysis and representation of the patient's medical data (Kartakis et al., 2012).

Wearable sensors Wearable sensors can be used to monitor people 24 hours a day and 7 days a week. Such systems are not just for monitoring, and they can also affect vital functions and deliver therapy. Wearable sensors are difficult to install on the body and require professional adjustments (Pantelopoulos and Bourbakis, 2010). Wearable sensors should be small and lightweight, in order to be fastened to the human body without compromising the user's comfort and allowing her/him to perform common daily life activities without restrictions. These devices can assess sounds, images, body motion, and ambient parameters (light, temperature, humidity, etc.), vital signs (blood pressure, respiration, body temperature, heart/pulse rate, body/weight/fat, blood oxygenation, ECG, etc.), sleep patterns and other health parameters, daily activities, and social interactions. The software elaborates a personalized profile of the user's physical and physiological patterns from the collected motor activity and health data to detect emergency situations. Wearable sensors are used for early detection of changes in a patient's status (Patel et al., 2012).

Motion accelerometers and gyroscopes can provide quantitative measurements and respond to both acceleration for gravity and acceleration for body movement. This makes them suitable for measuring postural orientations as well as body movements. Today, most smart phones are equipped with various sensors such as accelerometers, gyroscopes, proximity sensors, and global positioning systems (GPS), which can be used for detecting user activity and mobility. Other devices can be placed on almost any part of the body: wrist, ankle, waist, chest, arm, legs, etc. These sensors can detect many different variables such as speed, distance, steps taken, floors climbed, and calories burned.

Vital parameter Physiological measures of interest include heart rate, respiratory rate, blood pressure, blood oxygen saturation, and muscle activity. Parameters extracted from such measures can provide indicators of health status and have important diagnostic value. Noninvasive wearable medical sensors in the form of patches, small holter-type devices, body-worn devices, have been developed to monitor health signals. For example, blood glucose, blood pressure, and cardiac activity can be measured through wearable sensors embedded in common objects such as gloves, rings, necklaces, brooches, pins, earrings, and even belt buckles.

(Patel et al., 2012) Smart garments or E-textiles promise the most noninvasive form of health monitoring. They can monitor parameters such as, heart rate, blood pressure (BP), body temperature, galvanic skin responses, and can even perform electrocardiograms (ECG) for example SMARTEX¹ and LIFE².

The combination of wearable and ambient sensors is of great interest when monitoring older adults while deploying interventions to improve balance control and reduce falls. For example, one might be interested in using wearable sensors to track motion and vital signs. Specifically-designed data analysis procedures would then be used to detect falls via processing of motion and vital sign data. In this context, ambient sensors could be used in conjunction with wearable sensors to improve the accuracy of fall detection and, most importantly, to enable the detection of falls even at times when subjects do not wear the sensors.

Telemonitoring systems and Robots Smart homes are often associated with telemonitoring systems and robotics. Telemonitoring has the potential to provide safe, effective, patient-centered, timely, efficient, and location-independent monitoring. Some examples are shown below.

Philips has developed *TeleStation*³, a system that automatically collects vital sign data from wireless devices, then securely transmits data either by land line or cellular network, prompts patients to answer health assessment survey questions, and automatically sends follow-up surveys to clinicians.

Bosch has developed The *Health Buddy*⁴ telehealth system that enables patients in post-hospitalization or those living with chronic conditions to maintain regular contact with their Care Managers from the comfort of their homes. The Health Buddy System monitors a patient's vital signs and symptoms, educates the patient about his/her condition, and engages the patient in ways that lead to better self-management.

Intel has developed the *Health Guide*⁵ system: a comprehensive personal health system that promotes greater patient engagement and more efficient care by combining an in-home patient device with an on line interface, allowing clinicians to monitor

¹<http://www.smartex.it/en/>

²<https://www.x10y.com/>

³<https://tinyurl.com/yaxrhqbx>

⁴<https://www.bosch-healthcare.com/en.htm>

⁵<https://www.intel.com/pressroom/archive/releases/2008/20081110corp.htm>

patients and remotely manage care. The Intel Health Guide allows each patient to participate in a health session personalized for his or her specific situation. These sessions are designed and scheduled by the patient's healthcare professional. During each session, patients may measure their vital signs, respond to health assessment questions, and receive educational information and motivational messages.

The robots in smart homes may provide useful services and/or act as companions to ease the burden of social isolation (Chan et al., 2008). Recently, several robots have been developed in assisted-living environments for elderly people. They can support basic activities (getting dressed, bathing, toileting, eating) and mobility, providing household maintenance, monitoring of those who need continuous care and maintaining safety. A number of research institutes and companies have started to design and test healthcare robots for the elderly. Healthcare robots can be broadly categorized into those that provide physical assistance, those that provide companionship, and those that monitor health and safety.

An example of a robot more directly involved in healthcare is *Pearl*, designed to guide older people around the home and remind them of doctors' appointments and to take medications (Pollack et al., 2002).

Aibo is an entertainment robot developed and produced by Sony. It has been used extensively in studies with the elderly in order to try to assess the effects on the quality of life and symptoms of stress (Fujita, 2001).

Paro is a soft seal robot developed to study the effects of Animal Assistive Therapy with companion robots, and is targeted at elderly population (Wada and Shibata, 2007). It can provide company to elderly people who are living alone. It can perceive its environment with the help of five types of sensors: temperature, tactile, light, sound, and posture sensors (Aminuddin et al., 2016).

The *iCat* has been developed and is produced by Philips, its design aim is to be a research platform for human-robot interaction. It has a cat-like appearance and a face that is able to express emotions (van Breemen et al., 2005).

Hector It is a machine-like robot with a touchscreen interface. It provides aids for recording daily routines, controlling the environment, cognitive training, reminding to take medication, reviewing of daily agendas, detecting falls, and providing help during emergencies (Lera et al., 2014).

IRobiQ It is human-like Korean robot with a static face. The height of the robot is approximately 0.3 m. The robot helps the users with medication reminders, cognitive

training, entertainment, telepresence communication, and vital signs monitoring (Robinson et al., 2014).

2.7 Open challenges of continuous automatic assessment

From the analysis of current medical practice and research activities, I identify a set of open issues that motivated my work as described in the next chapters.

- *What are the minimal requirements?* For an effective continuous assessment of patients motility the observation needs to be carried out for some time to be able to capture meaningful information and associate reliable estimates.
- *How to guarantee a good spatial-temporal coverage of the continuous assessment?* A technical challenge one needs to face involves the complexity of analyzing day and night indoor environments of variable sizes and complexities.
- *How to merge and complement automatic continuous assessment and sporadic domain-expert analysis?* It would be useful to merge information coming from sensors and coming from the qualitative analysis performed by physicians.
- *How to incorporate the patient's specificities?* System calibration and tuning is necessary to meet the specificity of a given environment or situation. This would mean adjusting parameters and fine tuning the system to better reflect the user's habits.
- *Can home-like facilities participate in more general healthcare data collection?* Healthcare data come from very heterogeneous sources and they are often difficult to integrate.
- *How to satisfy user needs, acceptability and satisfaction?* Satisfying the needs of the user is a major challenge, especially with elderly patients. It is important to choose the suitable technologies, which will help the elderly to express their needs, improve their quality of care and comfort.
- *How to guarantee reliability and efficiency of sensory systems and data processing software?* One of the major problems remains the reliability of measurement

systems. Home care systems must provide reliable positioning and measurement of a patient's vital signs, have a reliable algorithm for evaluating the patient's "lifestyle" and trigger an alarm in case of danger;

On this respect, the outcome of an automatic assessment of frailty could be a meaningful complementary part of this general picture, providing additional information and automatic measurements for a better tailored treatment and follow-up.

Chapter 3

Mo.Di.Pro. Model of Protected Discharge

This chapter describes in detail the prototype of the model of protected discharge facility and the various sensors installed inside it.

The chapter is organized as follows. In Sections 3.1 and 3.2, I will describe the facility and the sensors installed in it. In section 3.3, I will discuss the process of data collection.

3.1 Introduction

The prototype is located within a local hospital and it was built according to the Ambient Assisted Living (AAL) approach in order to provide a home-like comfortable atmosphere while preserving the safety characteristics of a hospital room. The apartment consists of two bedrooms with private bathrooms, a gym, and a common area with kitchenette and living room. It is equipped with a set of environmental and wearable sensors to monitor the overall well-being of the patients. Technological devices and sensors have been integrated as much as possible into the furniture set in order to give a familiar appearance to the environment. The facility layout has been clearly divided into daytime and night time areas, and a design study was conducted to choose the appropriate colors, furnitures and arrangements. Starting from the study of users' needs, all the adopted solutions allow the integration of architectural design with the monitoring system. The common area hosts the majority of the ambient sensors, which I will explain them in detail in this chapter, they include

RGB-D sensors, cameras, localization tags, Passive Infra-Red sensors and medical devices. For privacy concerns, cameras and RGB-D sensors are not located in the bedrooms and bathrooms but, thanks to tags and presence sensors, it is possible to perform a unobtrusive monitoring of the patients in these areas as well. Automatic medical devices are located in a console table in the living room, and patients are asked to perform medical measurements twice a day. Each patient is also asked to play a VR game, which runs on a standard tablet, for cognitive assessments.

3.2 Concept

The prototype is a post-hospitalization protected facility built within the hospital, where the patient can be monitored by a system of sensors, while physicians and nurses have the opportunity of monitoring him or her remotely. Safety has been guaranteed by the possibility of remote monitoring and by the fact that the facility is hosted within the institution with easy access to all emergency and hospital facilities. The facility is equipped as a comfortable apartment, where volunteer patients at risk of Delayed Hospital Discharge (DHD) may spend some days after hospital discharge. The system includes the possibility for the doctors to access live information remotely. The apartment is located at the third floor of the E.O. Ospedale Galliera of Genoa, Italy. Figure 3.1 shows the starting point of the project. With the help of architects and geriatricians, we chose an area of a regular recovery unit suitable for the construction of the facility.

As shown in Figures 3.2, 3.3 and 3.4 the apartment consists of two bedrooms, one with a bed and a sofa-bed (for an accompanying person) and one with two beds (patient and caregiver), a gym, and a common area with kitchenette and living room. To provide a home-like comfortable atmosphere, a design study was conducted to choose the appropriate colors, arrangements and furniture, leading to an environment more similar to a regular apartment rather than a hospital room. The choice has been made to experiment with a domestic environment using materials, furniture, accessories and technology platforms already available in the market. Technological devices and sensors have been integrated as much as possible into the furniture set in order to give a familiar appearance to the environment. Starting from the detection of users' needs, all solutions and products adopted allow the integration of architectural environment with systems of monitoring, control and assistance (with particular attention to privacy), involving different technological areas such

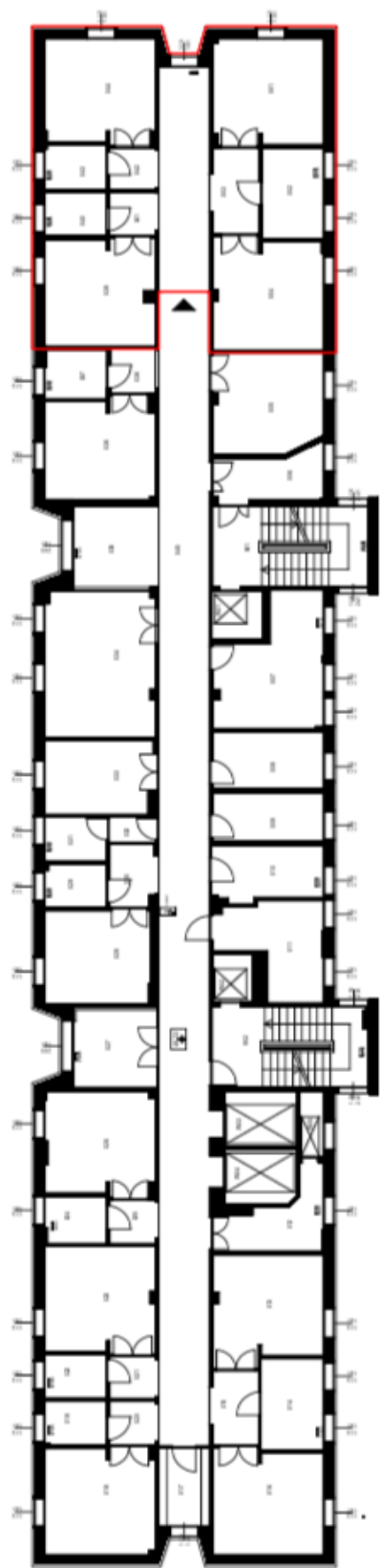


Figure 3.1 Third floor of the Galliera hospital, starting point of my project. The red line indicates the chosen area for the construction of the smart facility.



Figure 3.2 Apartment plan with description of the spaces.

as: telecommunications, computer science, microsystems, robotics, new materials, according to the AAL approach (Wichert and Eberhardt, 2012). A telepresence robot (see Figure 3.5) has also been used to allow guests and caregivers to communicate with doctors and researchers outside the apartment with actions-reactions in real-time voice and video.

The integration of "passive" solutions and "active" hi-tech systems makes it possible to implement smart environments, which are still designed to be perceived as domestic and in which the comfort and safety of the guest and caregiver is guaranteed and at the same time monitoring and care are optimized (Pierce, 2012). The apartment layout (see Figure 3.2) has been clearly divided in daytime and night time area, and defined by the use of cold and warm colors, to separate clearly the public spaces from the private ones (Gazzola, 2011), (Santagostino, 2006). Color has been used as signage and orientation to accentuate the differentiation between the different spaces of the accommodation and the transition from one to another. The light fixtures were predominantly composed of domestic purpose lights (such as floor lamps and lampshades over nightstands). The lighting during the night, for the safety of our guests, was guaranteed by a LED step light for orientation, automatically operated by getting out of bed. The apartment is equipped with a set of environment and wearable sensors controlling the overall well-being of the patients. The common area hosts the majority of ambient sensors, I will explain them in detail in the next sessions. The redundancy of sensors and measures to monitor similar activities is a design choice that guarantee the robustness of the results. The measurements can be further improved by integrating information



(a) Bedroom.



(b) Common area



(c) Kitchen



(d) Entrance

Figure 3.3 (a) shows one of the two bedrooms, (b) shows the common room, (c) shows the kitchen and the table area, (d) shows the entrance of the apartment.

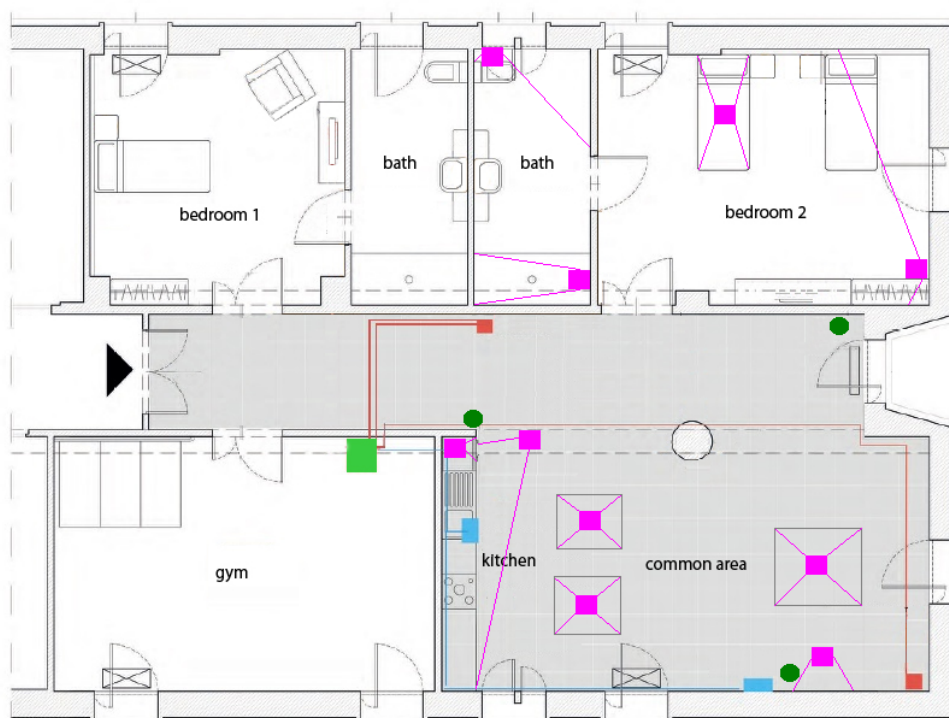


Figure 3.4 Apartment plan. Blue rectangles represent the RGB-D sensors, the small red squares correspond to the cameras. Green circles represent the localization tags, while purple rectangles indicate the Passive Infra-red (PIR) sensors and their field of view (through purple lines). They are all wired to the workstation (green square), placed in the gym.



Figure 3.5 The telepresence robot (PadBot P1), placed in the facility, allows guests and caregivers to communicate with doctors and nurses outside the apartment.

obtained from sensors distributed in the environment with measurements obtained by wearable devices (see Figure 3.4). We achieve a continuous monitoring of the patient's location and activity by analyzing the measurements obtained by sensors by means of appropriately designed signal processing and machine learning algorithms. The heterogeneous measurements are synchronized in time, but different sensors take care, in general, of specific aspects and no data fusion, up to now, takes place.

RGBD sensors are employed extensively in the analysis of the common area, mainly to evaluate motility and activities. The 3D skeleton data obtained from the RGBD sensors are used to locate people in the visible part of the scene and to associate a coarse status, based on the estimated people height encoded in the measurements, see Figure 3.6. This coarse status can take the following values: standing, sitting on a chair, sitting on the sofa, sitting on the floor. As a complement to these measurements, the localization sensor helps us locate one person on a wider area. As for the rest of the apartment, we can detect bathing sessions, which can be associated with movement in the shower area, detected by a presence sensor. We may also assess sleep quality based on the Passive Infra-Red (PIR) sensors located by the bed. We also take into consideration more complex activities, such as cooking and eating, involving the interaction with objects and the execution of a number of gestures (such as pouring water in a glass, or opening a cabinet), in a variable sequence. The concurrent and independent monitoring of objects and gestures of relevance for the task allows for a richer representation of such activities, and therefore a more robust recognition. In the remainder of the chapter, I will describe in detail the characteristics of the various sensors installed in the facility and the data collection process.

3.2.1 Vision sensors

Figure 3.7 shows the arrangement of the visual sensors in the living room of the apartment, highlighting their fields of view and overlaps. The RGB-D sensors (see Figure 3.11b) are Asus Xtion Pro, with only the depth channel available. This choice allows the possibility of using them also in the bedrooms, thus avoiding privacy issues (Banerjee et al., 2012). Each sensor acquires a depth stream with VGA resolution (640x480 pixels, at 30 fps). They cover a field of view of about 58deg horizontal, 45deg vertical and 70deg diagonal, with a range of operation between 0.8m and 3.5m. The first RGB-D sensor (RGBD₁) is located over the kitchen's sink.

Its field of view (FOV) is highlighted in blue in Figure 3.7, right, and it covers all the kitchen and table area, i.e., where patients are supposed to have breakfast, lunch and dinner. The second one (RGBD₂) is located near the TV in front of the sofa, its field of view is highlighted in red in Figure 3.7, and it covers the living room, i.e., the sofa, the armchair, the library, and the area of the vital monitoring devices. It is worth noting that, in order to accomplish some design constraints without affecting the appearance of the room, RGBD₁ and RGBD₂ are located at different heights from the ground floor. Each RGB-D sensor is connected via USB to a small PC, i.e. a home theatre PC, again chosen to be less intrusive and noisy, running Ubuntu OS, and the acquisition software developed by us.

The cameras (see Figure 3.11a) are high resolution mini-dome IP cameras acquiring 1920×1080 frames at 25 fps. They are located in the two opposite corners of the room, indicated in red in Figure 3.7. The relative positions of the RGB-D sensors and cameras is intended to provide a partial overlap of the fields of view while covering complementary areas. The two home-theatre PCs and the cameras are connected to a local ethernet network.

The sensors have been calibrated to provide synchronized video streams (from the cameras), depth maps, and three-dimensional skeletons of the people present in the scene. The 3D information is aligned with a common reference system, by exploiting the overlapping areas seen by the sensors. The streams coming from the RGBD sensors are analyzed using the OpenNI SDK (ver. 1.5.2), which allows to robustly estimate the presence of people in the scene, and the evolution in time of the 3D coordinates (x, y, z) of a set of body joints (see Figure 3.6). In my analysis, I focused on the head joint because of its stability. A precision of about 5 cm is guaranteed in normal acquisition conditions. To facilitate access to these large amounts of data and to control the space requirements, we record flows of 3D data (for all the skeleton joints) when a dynamic events is occurring (that is, when the presence of a skeleton is detected).

3.2.2 Virtual Reality based device for cognitive assessment

Taking inspiration from existing works in the literature, and considering an everyday life task, I implemented a virtual supermarket for tablet devices. The environment is composed of three shelves, containing several common life items. The layout of the scene, the dimension of the items and of the text, and all that concerns the user

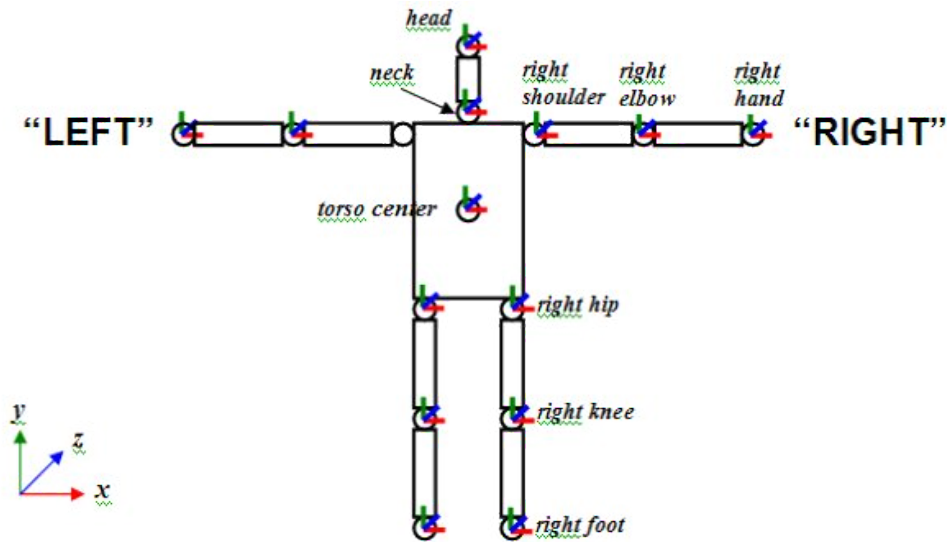


Figure 3.6 The joints recognized by the Asus RGBD sensor and the OpenNI SDK. For each joint, the 3D position with respect the sensor, and according to the axes highlighted in the figure, is computed.

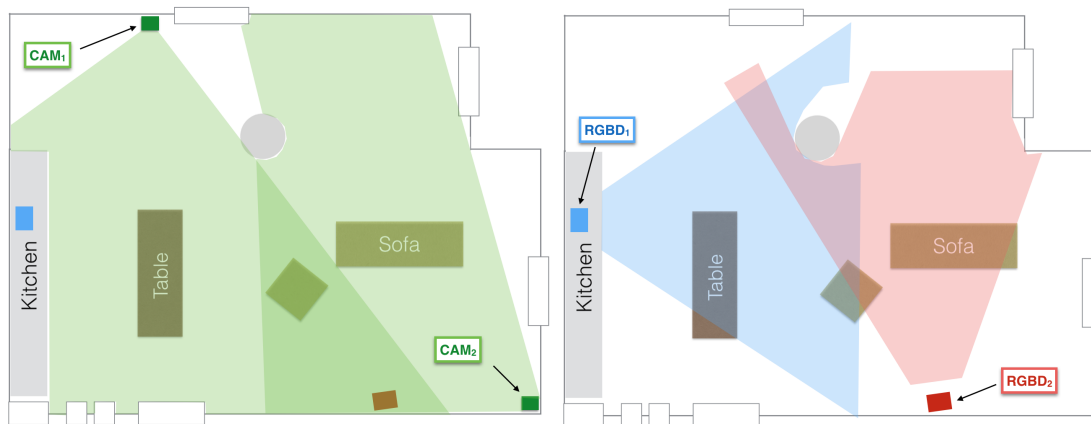


Figure 3.7 A sketch of the visual sensors fields of view and their overlap. The left panel shows the field of view of the two cameras, while the right panel shows the field of view of the two RGB-D sensors.

interface have been discussed with the geriatrics medical staff. The game runs on a 10,1-inch Samsung Tab 4 with a 1,2 GHz Quad-Core processor and Android 5.0.2 operating system. The game was created with Unity 3D¹, a cross-platform game engine for the development of 2D and 3D video-games for desktop, web and mobile devices. Most of the items in the game were made with SketchUp², a 3D modeling software commonly used to design realistic 3D objects or to download them from a free library (3D Warehouse) and export them in a Unity-compatible format. Figure 3.8 shows a sketch of the "Supermarket" virtual environment, and of the cognitive assessment procedure using the developed tool. The game is composed of three scenes: a menu, a demo scene, and the main scene. The menu allows the subject to choose whether to try the demo scene or to go directly to the game. The demo scene is a simplified version of the main scene and its aim is to explain the game to the player and to allow him/her to learn how to interact with objects and buttons. Each patient is asked to perform the VR game, which consists of a virtual supermarket with two shelves and a fruit counter. The patient has to perform two tasks. The first one consists in buying all the items on a shopping list, the items are randomly chosen when the game starts; and the second task consists in paying the exact total amount. We designed the game in order to keep the interface as simple as possible. The patient cannot freely navigate the scene but he/she has to turn the camera toward the selected shelf using the arrows at the bottom of the screen. Only when he/she is in front of the desired shelf, he/she can interact with the items on it, for example by clicking or tapping on one of them, a pop-up window with the product name is displayed and the player is asked if he/she wants to add that article to the cart or not. The VR game is developed on a standard tablet, which is used both to display the game itself and to compute some parameters to be used by the doctors to assess the cognitive status (see Section 5.5). In this way, the correctness of the required tasks (i.e. to select the elements starting from a given list, and to pay the correct amount of money) is evaluated and correlated with the cognitive status of the patient. It is worth noting that this evaluation can be performed by using an ecological task inspired by common actions of every-day life (i.e. going to the supermarket).

3.2.3 Health devices and distributed ambient sensors

¹<https://unity3d.com/>

²<https://www.sketchup.com/>

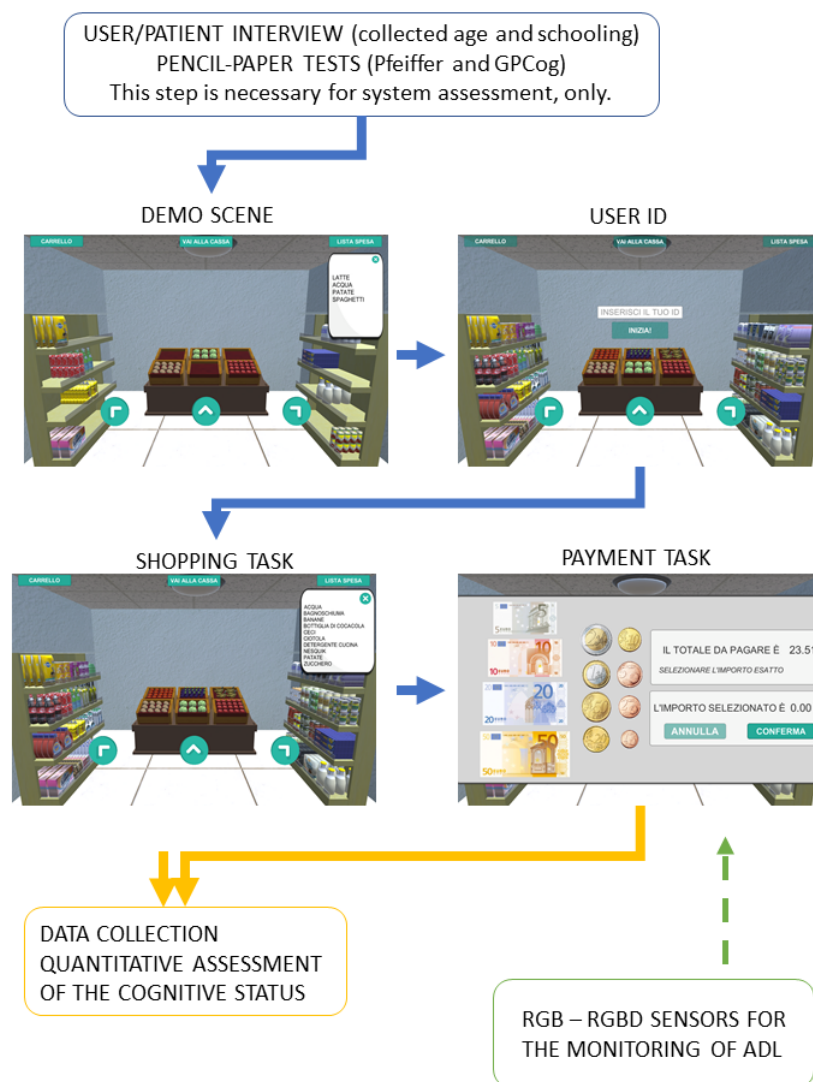


Figure 3.8 A sketch of the "Supermarket" experimental setup, based on a standard tablet.

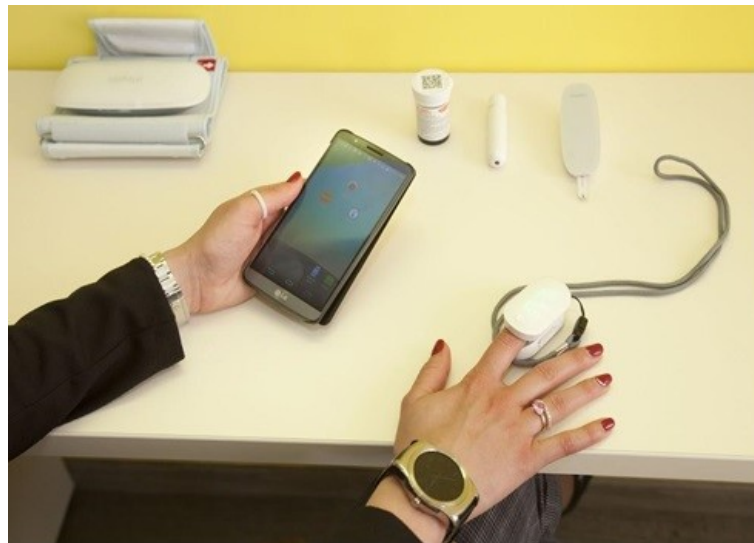


Figure 3.9 Vital monitoring devices. From left to right, clockwise: blood pressure monitor, glucometer, oximeter and smart phone

Health monitoring sensors The physicians identified a minimal set of vital parameters to be monitored, including weight, blood pressure, heart rate, Oxygen saturation SpO2 level, glucose. They recommended these parameters to be measured twice a day directly by the patient. Based on these requirements, I identified a set of wearable and non-invasive devices, selected to guarantee the patient's complete freedom of movement (no cables, data are transmitted via wireless communication) and to allow for an automatic analysis of the acquired data (this involves the transmission of the collected data to a remote workstation running an appropriate management software). All the equipment is organized on a monitoring console table, to be used by the patients. The available devices are shown in Figure 3.9 and they are all provided by iHealth Labs¹. This brand was preferred to competitors as all chosen instruments are CE marked medical devices, they are very user-friendly, data are recorded via an app (see Figure 3.10), and all acquired raw data are available in .csv and .xls format, ready for further analysis. The collection of all measures is done via bluetooth by an LG G3 smart phone, which sends the data to a platform, which stores the data and also allows physicians and nurses to remotely monitor the parameters.

¹<https://ihealthlabs.com/>

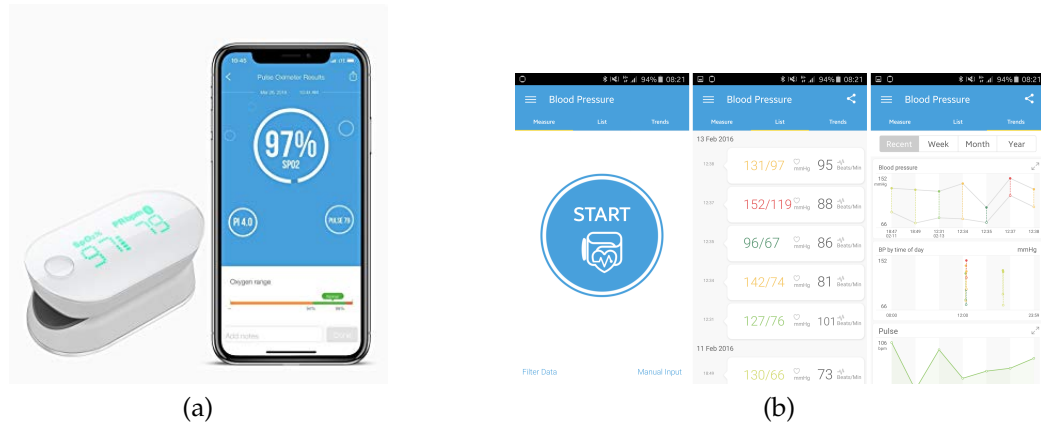


Figure 3.10 Example of iHealth app, figure (a) shows the SpO2 measure automatically recorded by the smartphone, and figure (b) shows the pressure measure.

Distributed sensors The localization system, Eliko KIO RTLS¹ (Figure 3.11c), is a Real Time Locating System (RTLS) based on the Ultra WideBand (UWB) technology, which allows for a positioning precision of about 30cm. The system is based on the "tag and anchor" paradigm, which assumes the tag to be always attached to the person and the anchors to be in fixed, a-priori known locations in the environment (green dots in Figure 3.4). Those sensors allow us to obtain localizing information also outside the internal area delimited by the anchors (i.e.: the common area), but with lower precision. The (X, Z) position of the tag is then estimated in real-time on the basis of its distance from the anchors. The system allows for a continuous and unambiguous tracking of the monitored person.

The presence sensors, Aeotek MultiSensor 6² (Figures 3.11d and 3.11e), are devices integrating six channels, among which we are currently exploiting the Passive Infra-Red (PIR) and the light sensors. Those have been placed in different locations (in purple in Figure 3.4) and calibrated in such a way to monitor disjointed locations. Particular attention has been placed on the recognition of kitchen activities, with sensors placed in a cabinet of the kitchen and in the tables area, but also close to the sofa, in the bathroom, and in the bedroom.

Chair occupancy sensors, SparkFun Force Sensitive Resistor (Figure 3.11f), detect whether there is a load or not on the chair by monitoring the pressure level measured below its legs. The detection of the movement and the recognition of gestures performed by the patient can be improved by integrating information obtained from

¹<http://www.eliko.ee/products/kio-rtls/>

²<http://aeotec.com/z-wave-sensor>

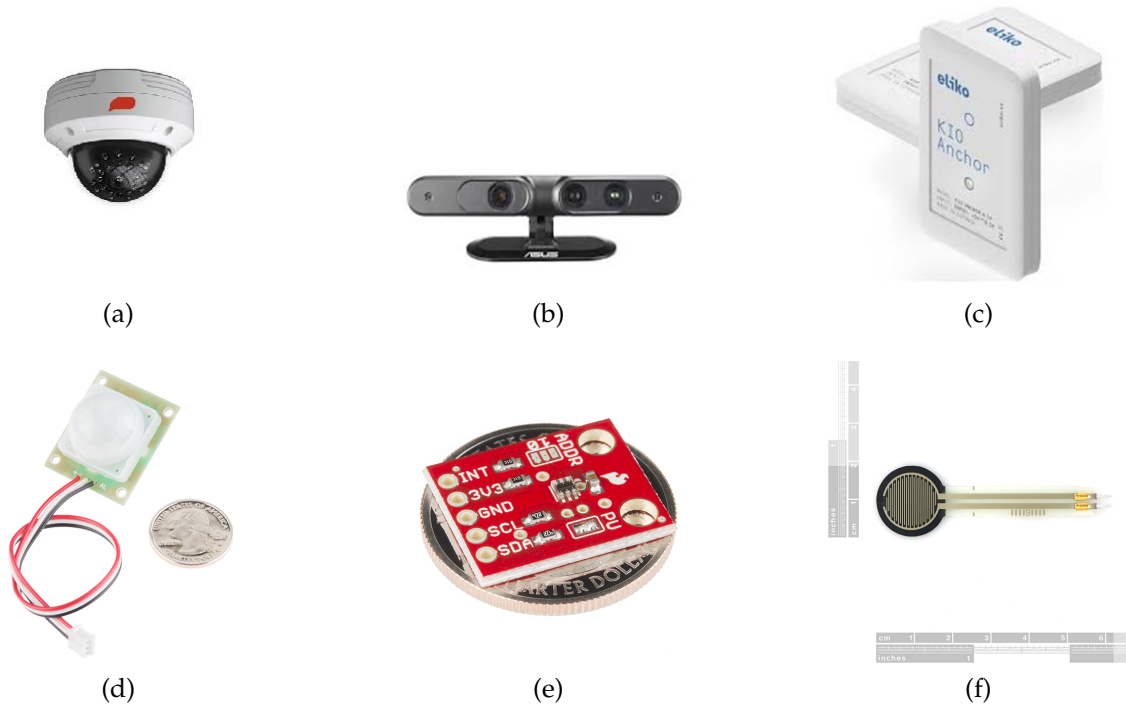


Figure 3.11 Some of the sensors used. From top left, clockwise: (a) mini-dome camera, (b) ASUS Xtion Pro RGBD camera, (c) ELIKO KIO RTLS localization system, (d) SparkFun PIR Motion Sensor, (e) SparkFun Luminosity Sensor and (f) SparkFun Force Sensitive Resistor.

sensors distributed in the environment with measurements obtained by wearable accelerometers. So far, we have used a LG G Watch R5 (Figure 3.9) equipped with a triaxial accelerometer.

3.3 Data Collection

Calibration At the beginning of the project some volunteers spent some days in the facility to calibrate the data acquisition system. I taught them how to use the provided devices and I continuously asked for feedback about the comfort of the apartment and the usability of the technology. A second session of data acquisitions was carried out with young volunteers who stayed in the apartment for a few hours, responding to specific requests for movements. This second group of volunteers was used to train the monitoring system.

Test Once it was established that the system was mature and safe enough to accommodate elderly volunteer patients, I began, under the supervision and support of the physicians, to test the system's performance starting new data acquisitions with elderly guests. The volunteers and patients recruitment plan was established together with the geriatricians, starting from the medical case reports and the nurse diary of the Internal Medicine Unit of the hospital. When the patient has been considered clinically dischargeable from the hospital but unable to return to his/her home for non-health reasons, he/she is offered to give his/her informed consent and temporarily transfer his/her residence to the facility for a period not exceeding five days. The patient was also asked to identify a person ("caregiver") who could stay with him/her during the period of residence at the facility in order to help him/her in managing any non-medical needs during the night hours. During the check-in the patient was provided with a "kit" including a smartwatch, a smartphone, and a localization device. For the entire duration of stay, location/movements/actions of the guests have been recorded in order to create predictive models for the study of important events from the clinical/pathological point of view. The above data have been detected through the system of position and movement sensors installed in the facility. My task during this phase was to explain and teach elderly patients how to use the technological devices provided in the facility, especially the medical ones. Five patients were recruited following this strategy, but some problems were found due to the difficulty of using medical devices by voluntary patients and the management of hospital staff, especially during the night hours. In particular, the elderly were struggling to use the technology provided and they often forgot the instructions provided (for example, measure the clinical parameters twice a day). Moreover, the fact that the apartment was located inside the hospital walls, meant that the medical staff had full responsibility on the guests, thus involving frequent checks and consequently an overload of the nurses' work, especially during night shifts.

Experiments Given the previous observations, together with the doctors, I decided to recruit healthy elderly volunteers to stay in the apartment for a few hours. This obviously led to the waiver of clinical measures and related statistics. Twenty-four volunteers participated to this phase of experiments. I taught all the volunteers how to use the technology provided in the facility. I analyzed the data collected by the sensors and I computed some statistics based on them. Fortunately, I obtained

encouraging results even if the time I had to collect the data was restricted, because of the problem mentioned above. All the results I obtained with my analysis are shown in Chapter 5.

Ethical aspects The research protocol complies with the principles established by the 18th World Medical Assembly in Helsinki, 1964 and subsequent amendments/additions and with the Good Clinical Practice.

Informed consent. Each patient should be informed about the nature of the study, its purpose, procedures, expected duration, potential risks and benefits. Each patient must be informed that participation in the study is voluntary and that he/she can withdraw from the same at any time. The withdrawal of consent will not affect his subsequent clinical treatment or relationship with the doctor. Informed consent will be drawn up by the coordinating center by means of a standard written declaration, using non-technical language. The patient must demonstrate that he/she has understood the information contained in the consent, signing and dating it; in addition a copy of the document must be provided to him/her. No patient can be enrolled in the study before his/her informed consent has been obtained. An original signed copy of the patient's written consent must be kept by the recruiting center in a special section of the study documentation.

Privacy. Patient names will not be registered, but each subject will be identified with a number: this number will identify the patient and must be included in all databases for data collection and analysis. In order to avoid identification errors, the initials of the patients (maximum 4 letters) and the date of birth must be reported in the data collection forms to identify the subjects. Study researchers ensure that all persons involved in the study will respect the confidentiality of any information regarding the participant on the trial. All the parties involved in the study will keep the utmost discretion to ensure that neither the person nor the privacy of the patient's family are violated; appropriate measures will be taken to prevent unauthorized access to study data. The processing of personal data of the patients participating in the trial, and in particular the related data regarding the consent, will be compliant with local privacy laws: D. Lgs. 196/03 and subsequent amendments ("Privacy Code").

Chapter 4

Methods for automatic assessment

This chapter describes the monitoring system, the process of data acquisition and analysis. In particular, the chapter focuses on the method used to obtain information on the localization of the person and how the other motility quantities are evaluated in order to obtain the formulation of the Motility Index.

4.1 Introduction

In this chapter, I describe the approaches I propose for the automatic assessment of motility. Figure 4.1 shows the pipeline of my monitoring system, from the acquisition and processing stages, to the computation of the motility quantities, and finally to the estimation of the Motility Index. When the RGB-D sensors detect the presence of an individual in the scene they send a trigger signal to the cameras which also begin the acquisition. Data are then stored on line in a database that makes them available for future off-line analysis.

Physicians, in particular geriatricians, use questionnaires and evaluation scales, in order to assess the mental and physical status of patients. Based on the results of these evaluations they estimate the Multidimensional Prognostic Index (MPI) of elderly patients (see Section 2.2.2). In this chapter, I will focus on the Exton Smith Scale (ESS), a 5-item questionnaire that is part of the MPI and allows the doctors to determine physical condition, activity, and motility of the patient. The aim of my work is to automatically estimate related measures in terms of motility, activity distributions, and postural transfers. In particular, I compute a set of motility quantities, identified with the help of geriatricians. These quantities are empirically estimated through the analysis of the data coming from the RGB-D sensors. The first

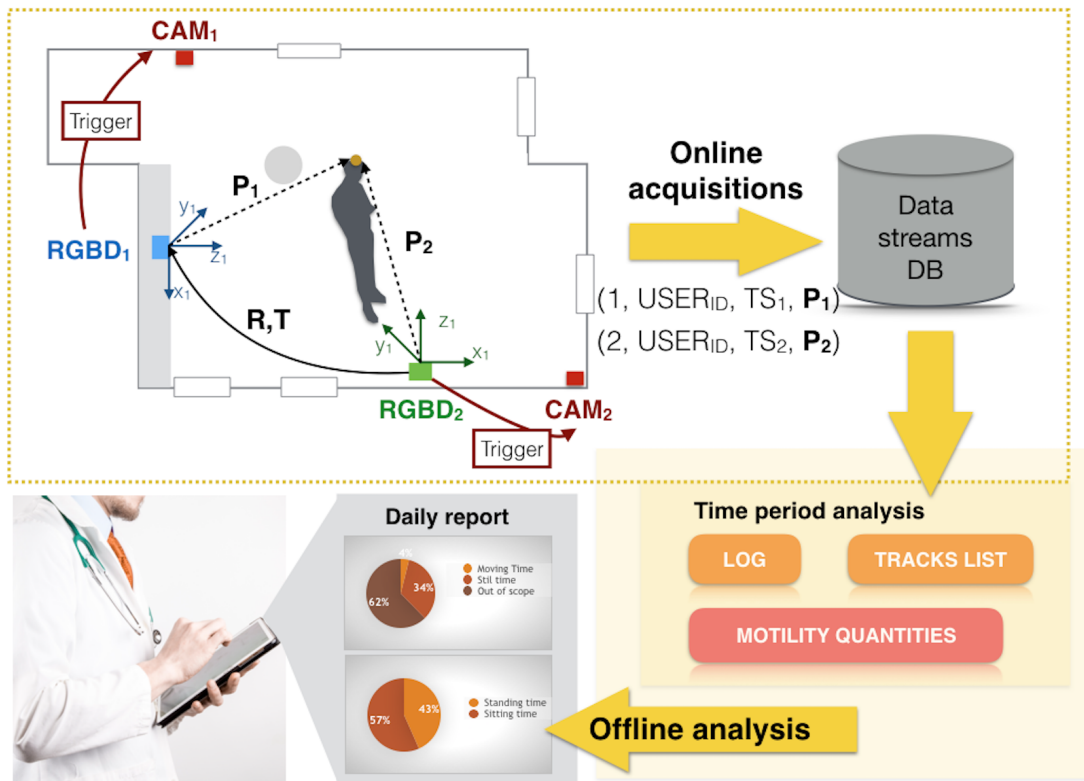


Figure 4.1 A visual sketch of the pipeline of my system. When the RGB-D sensors detect the presence on a human in the scene, they trigger the corresponding camera that starts the acquisition. Data are stored on-line in a database that makes them available for future off-line analysis.

task is localization, whose goal is to determine, at each time instant, the position of a person in the apartment. For this task I used the information coming from the RGB-D sensors providing the evolution in time of the (X, Y, Z) coordinates of the body joints. Then I compute tracks detection, a track is a continuous set of adjacent observations where the dynamic and postural state of the subject is unaltered. A new track is detected when the user is (re-)entering the scene, his/her posture is subject to a transition or his/her velocity rapidly increases or decrease. Once I have evaluated the motility quantities I combine them in a single value, called the Motility Index (MI), summarizing the overall level of dynamism of the observed subjects. The formulation of this MI is coherent with the MPI: it takes a value between 0 and 1, approaching 1 when the motility of the subject is not satisfactory. The Motility Index allows us to compare my automatic data analysis with the qualitative assessment performed by physicians.

4.2 Evaluating the motility of patients

With the help of geriatricians, I identified a set of motility quantities that can be computed automatically and reliably from RGB-D streams:

- number of postural changes, i.e. from sitting to standing and vice-versa;
- the total time spent moving and still (in seconds and in percentage);
- number of instance of walk, i.e. how many times, in a given observation period, a person starts walking;
- average distance and velocity of a single walk;
- total distance walked, over an entire observation window
- longest distance covered in a single walk;
- longest walking time.

All these measurements contribute to compose the MI, as we will discuss later in this section. In the following, I will show how data are acquired and prepared for future analysis. Afterwards, I will provide the details on the estimation of the motility quantities.

4.2.1 Data acquisition, storage and preprocessing

The software for the acquisition from each RGB-D sensor runs continuously on the workstation. In the presence of people in the field of view, they acquire and store the 3D position of the skeleton joints for each user, which is assigned a unique identifier. The associated timestamp is also stored for future reference. The two RGB-D sensors produce independent yet temporally related streams of acquisitions – each one with respect to its own reference frame – and depending on the position the user may be associated with one or two simultaneous joints observations.

Observations are stored as tuples of the form

$$(RGBD_{id}, TimeStamp, USER_{id}, JP_1, \dots, JP_N),$$

where $RGBD_{id} = \{1, 2\}$ identifies a sensor, while $JP_i = (X_i, Y_i, Z_i)$ is the 3D position of the i -th joint in files covering ΔT minutes of acquisitions, in my work $\Delta T = 30$.

Although I acquire all the skeleton joints, in this analysis I only take into account the head joint, since it meets the requirements of stability and precision for our reference application (Canessa et al., 2014; Clark et al., 2012).

In order to be able to merge observations obtained from the two sensors, I need to adjust their space-time mutual relationship:

- The two sensors are accessed in a temporally synchronized way so that the two views correspond on time
- The reference systems of the two views are related by a global rigid transformation, a roto-traslation. I estimated this transformation by collecting simultaneous observations from the small intersection between the two fields of view and applying a DLT algorithm with RANSAC to cope with the presence of outliers (Hartley and Zisserman, 2003).

Given a temporal period of analysis \mathcal{T} , observations are pre-processed with the following steps:

- i We apply a roto-translation to all observations obtained by $RGBD_2$, to bring them to the reference frame of $RGBD_1$.
- ii We merge the observations from the two views by temporally ordering all the tuples; then, for all observations occurring within a second, we compute the average position. We also apply a smoothing on the transitions between the two views, while discarding the oscillations.
- iii In the presence of multiple users, we solve data association using the output of the localization sensors installed in the facility.

When detecting a human in the scene, the RGB-D sensor also triggers the acquisition from the corresponding camera. In the regular behavior of the system, the video streams are stored but accessible only if needed (e.g. for safety of the user) to guarantee the privacy of patients. In my investigation phase, videos are mainly used for a visual inspection allowing the validation of my results. Although they do not play a key role in my current investigation, cameras may be exploited for further analysis of ADL.

4.2.2 Localization

The first task I need to address, prior higher level analysis, is the localization of one or more users in a given observation time. The goal of localization is to determine, at each time instant, the position of a person in the apartment. For this task I used the information coming from the RGB-D *depth* sensors providing (X, Y, Z) coordinates of the body joints.

A qualitative overview of the space occupancy and of the localization obtained by the RGB-D sensors installed in the common room is shown in Figure 4.2a and 4.2b. The maps are computed automatically and incorporate information from the two different sensors, one of which is considered as a reference frame (blue dots), while the other is related to the reference frame through a rigid roto-translation transformation which is learnt from the data (red dots).

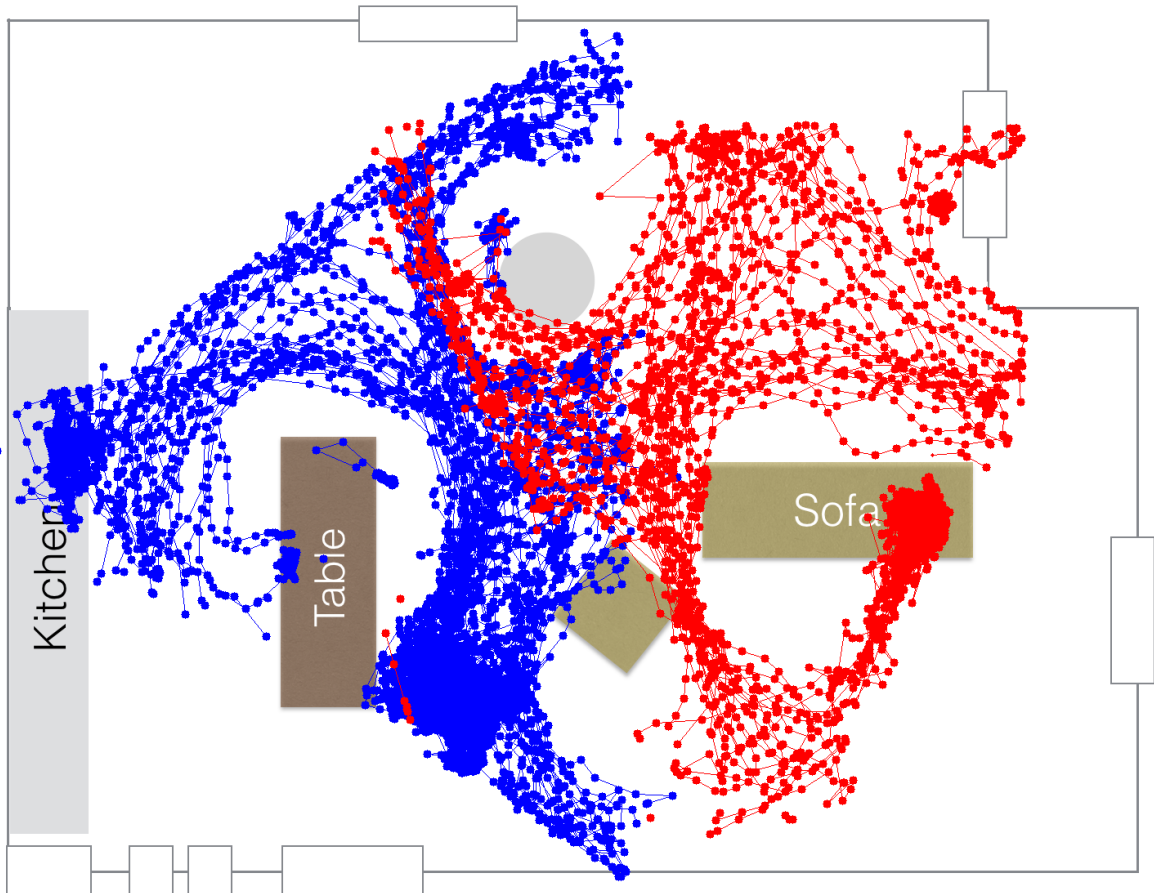
In Figure 4.2a, I report the projections of the head joint positions on the image plane representing a visual sketch of the environment. Projections have been obtained by estimating the homography between the X and Z coordinates of the head joints and their corresponding location on the image. Different colours refer to different RGB-D sensors. In Figure 4.2b, an alternative visualization highlights the space occupancy. From a visual inspection of both representations, it is possible to immediately identify common patterns of movement as well as an idea of the scene portions in which people spend most of the time. For example in the right corner of the table, in the rightmost part of the sofa or in the kitchen by the sink. As expected (see also Figure 3.7 right), there are a few blind spots. This issue can be easily overcome by integrating data from the cameras.

4.2.3 Motility quantities estimation

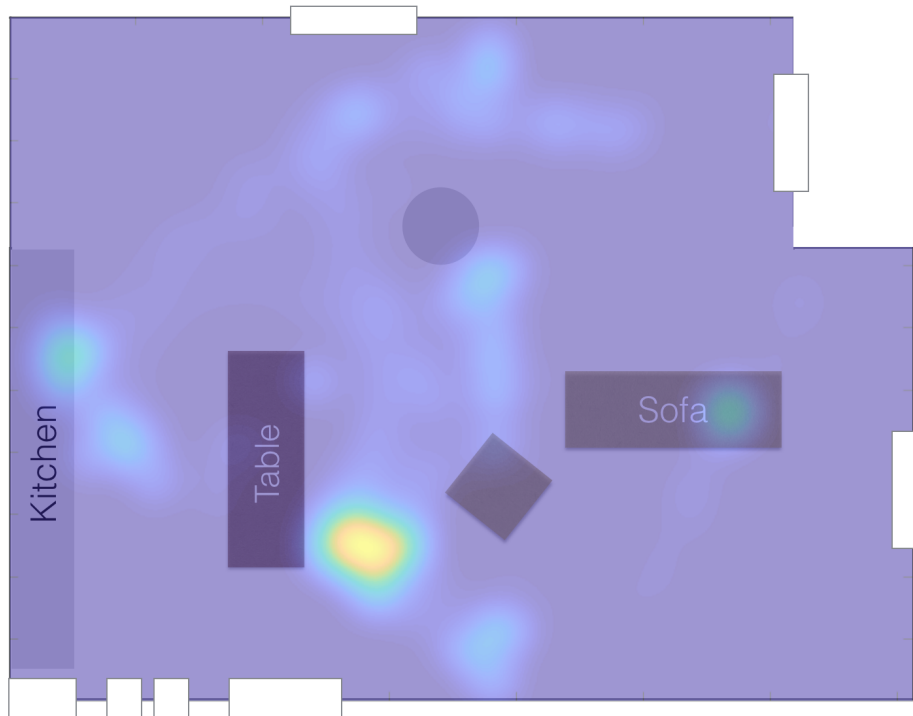
The result of the data preprocessing can thus be formalized as follows. Given the period of analysis $\mathcal{T} = [t_0, t_{\mathcal{T}}]$ and an observed user *id*, I first identify sets of joint observations consecutive in time (I am not guaranteed that the user remains visible by the sensors for the entire period of analysis). Formally, this amounts to identify a series of time instants

$$T_m = [t_{m0}, t_{m1}, \dots, t_{mk-1}, t_{mk}] \quad (4.1)$$

such that a pair (t_{mi}, t_{mi+1}) delimits a continuous interval of observations.



(a)



(b)

Figure 4.2 An example of distribution of head joints positions over time. (a) The trajectories of head positions projected onto an image plane representing the environment (blue and red refer to $RGBD_1$ and $RGBD_2$, respectively). (b) A heat map obtained from the points distribution of head joints positions over time.

Then I produce a temporal series of measures in the form

$$\mathcal{M}_{\mathcal{T}}^{uid} = \bigcup_{t_{mi}} \{\mathcal{O}_{t_k}^{uid}\}_{t_k=t_{mi}}^{t_{mi+1}} \quad (4.2)$$

with

$$\mathcal{O}_t^{uid} = (RGBD_{id}, TimeStamp_t, \mathbf{P}_t^{head}), \quad (4.3)$$

where $\mathbf{P}_t^{head} = (X_t^{head}, Y_t^{head}, Z_t^{head})$ is the 3D position of the head joint and time t , and $TimeStamp_t$ is the timestamp of time t .

For readability, in the future I will fix a user and omit the *id* and *head* references. Thus unless otherwise stated and without loosing in generality, my discussion will refer to the analysis of the head joint of a single user.

Now I address the problem of evaluating motility quantities used later to estimate the Motility Index of a user. Motility quantities are based on statistics on the joint observations included in the set $\mathcal{M}_{\mathcal{T}}$, and they may be computed at a global level on the time period \mathcal{T} or on sub-intervals, which I call *tracks*. In the following, I detail the computation of such statistics and discuss the experimental results.

Global motility quantities We analyze here measures that are global in a given observation window. Referring to the list reported in Section 4.2, from a global point of view, I aim at estimating the following:

- **Number of postural changes (TR_{2stand} , TR_{2sit}).** The estimate is based on the analysis of the Y (height) coordinate of the head joint, and its temporal variations. More specifically, I fix a threshold τ_y and an interval around it defining the range of values which identify a transition between sitting and standing posture or vice-versa. It is worth noting that such value strongly depends not only on the height of a person but also on the environmental elements and from case to case more than one value may be needed. For instance in our facility, I have to consider the presence of chairs and a sofa, for which the sitting postures are characterized by two different values of Y to distinguish the position of the patient, sitting on the chair or the sofa (see Figure 4.3(a)). The number of sit-to-stand transitions TR_{2stand} can be determined as the cardinality of the set collecting the time instants $t_i, t_0 < t_i < t_{\mathcal{T}}$, such that there is a $k > 0$ for which $Y_{t_i-k} < \tau_y$ while $Y_{t_i+k} > \tau_y$. The identification of the stand-to-sit transitions is straightforward.

- **Number of instances of walks (W).** I aim here at identifying the time instants in which the magnitude of the velocity of the joint goes above a certain threshold τ_v (see Figure 4.3(b)). To compute the velocity module I first approximate the instantaneous velocity components as the difference between consecutive joints 3D positions – i.e. $\mathbf{V}_t = \mathbf{P}_t - \mathbf{P}_{t-1} = (V_{xt}, V_{yt}, V_{zt})$ – and then computing the magnitude as $V_t = \sqrt{V_{xt}^2 + V_{yt}^2 + V_{zt}^2}$. The number of instance of walk W is computed as the cardinality of the set including the time instants $t_i | t_0 < t_i < t_{\mathcal{T}}$ for which is exists a $k > 0$ such that $V_{t_i-k} < \tau_v$ and $V_{t_i+k} > \tau_v$.
- **Number of instance of stops (S).** Similarly to the previous point, this quantity is estimated as the cardinality of the set including the time instants $t_i | t_0 < t_i < t_{\mathcal{T}}$ for which is exists a $k > 0$ such that $V_{t_i-k} > \tau_v$ and $V_{t_i+k} < \tau_v$.
- **Total time spent moving (TM) and still (TS).** Since $\mathcal{M}_{\mathcal{T}}$ includes observations averaged at a temporal resolution of one second, this statistic amounts to counting the number of observations in $\mathcal{M}_{\mathcal{T}}$ whose corresponding V is above or below the threshold τ_v , for moving and still instances respectively. Notice that only observations in which the subject is standing are considered for the estimation of this quantity.
- **Total time spent sitting (Tsit)** It is estimated as the number of observations for which the Y coordinate of the head is below the threshold τ_y .
- **Total distance walked (DW).** The total distance spanned by the observations in $\mathcal{M}_{\mathcal{T}}$ may be computed as the sum of all consecutive displacements between joints positions. In mys setting, such displacement corresponds to the velocity magnitude, thus

$$DW(Tk_j) = \sum_{t=t_j}^{t_{j+1}} \|\mathbf{V}_t\| \quad (4.4)$$

Notice that $TT = TM + TS + T_{sit} = \#\mathcal{M}_{\mathcal{T}}$, which amounts to the number of actual observations in the time period \mathcal{T} . In general, TT is lower than the length of \mathcal{T} since the subjects may spend some time out of the field of view of the sensors.

Tracks detection and track-based motility quantities A track is a continuous set of temporally adjacent observations where the *dynamic and postural state* of the user is unaltered. A new track is detected when the user is (re-)entering the scene, his

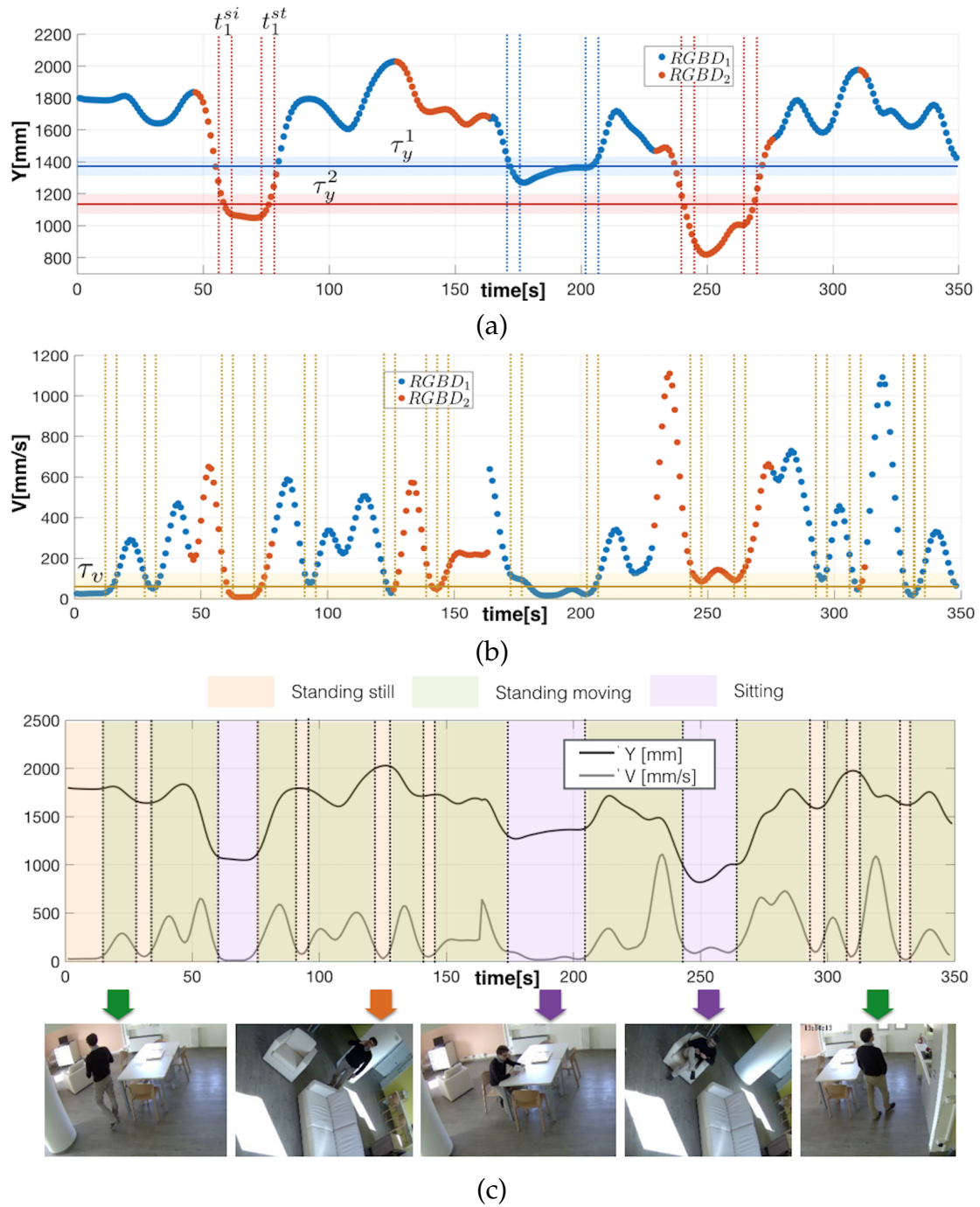


Figure 4.3 An example of temporal analysis of the head height (a) and its velocity (b). Posture and velocity changes are detected and used to identify tracks (c).

posture is subject to a transition from sitting to standing or vice-versa, or the velocity rapidly grows from zero to a reference value, indicating that an instance of walking is starting, or the opposite. It is straightforward to notice that the tracks can be easily identified by appropriately combining T_m (see Eq. 4.1) with all the time instants collected for computing the quantities TR_{2stand} , TR_{2sit} , and W , ending up with a sequence of ordered time instants $T_{tk} = [t_0, \dots, t_h, \dots, t_{\mathcal{T}}]$, where t_h is labeled according to one of the sets mentioned above. With this in mind, I can consider three different classes of tracks, corresponding the user *sitting*, *standing still*, and *moving*. The plot in Figure 4.3(c) reports an example of tracks detected and color-coded according to the reference class. In particular it can be noted that the *standing still* posture is characterized by a high value of Y but low value of V , *standing moving* is characterized by high value of Y and V , finally, the *sitting* posture is characterized by a low value of Y and V . Let me denote with $TK_{\mathcal{T}} = [Tk_1, \dots, Tk_M]$ the set of M tracks associated with the time period \mathcal{T} , where the j -th track is a serie of X and observations consecutive in time, $Tk_j = [O_{t_j}, \dots, O_{t_{j+1}}]$, with $t_j \in T_{tk}$. Only on tracks labeled as moving, I compute a set of statistics – with straightforward mathematical definitions summarized in Table 4.1 – as follows:

- **Average distance (AD) and average velocity (AV) of moving tracks**, see Eq. 4.6 and 4.8.
- **Longest distance (LD) covered in a single walk**, see Eq. 4.9.
- **Longest walking time (LT)**, see Eq. 4.10.

4.2.4 Motility Index estimation

Once I have evaluated the motility quantities, I combined them in a single value – called the Motility Index (MI) – summarizing the overall level of dynamism of the observed subjects. More formally, the index is estimated as follows

$$MI(\mathcal{T}) = (1 - \alpha) \left(\frac{T_{sit} + TS}{TT} \right) + \alpha \left[C \left(1 - \frac{TR_{2sit} + TR_{2stand} + W + S}{TT} \right) \right] \quad (4.11)$$

where the first term quantifies the percentage of inactivity time, while the second determines the relative amount of postural and dynamic transitions with respect to the entire time period. The parameter α is a value to be chosen to weight the

Table 4.1 A summary of the mathematical formulation for the tracks analysis.

Distance covered in a single track	$DW(Tk_j) = \sum_{t=t_j}^{t_{j+1}} \mathbf{v}_t $ (4.5)
Average distance	$AD(\mathcal{T}) = \frac{1}{M} \sum_{j=1}^M DW(Tk_j)$ (4.6)
Track length	$L(Tk_j) = \#Tk_j$ (4.7)
Average velocity	$AV(\mathcal{T}) = \frac{1}{M} \sum_{j=1}^M \frac{DW(Tk_j)}{L(Tk_j)}$ (4.8)
Longest distance	$LD(\mathcal{T}) = \max_{j=1}^M DW(Tk_j)$ (4.9)
Longest track	$LT(\mathcal{T}) = \max_{j=1}^M L(Tk_j)$ (4.10)

importance of the two terms of the equation, while C is a factor to make the second term numerically comparable with the first one. Similarly to the MPI, the Motility Index approaches 1 when the motility of the subject is not satisfactory.

Chapter 5

Experiments

This chapter is dedicated to the experimental analysis of the proposed methods. In particular, I describe a set of experiments I carried out on different user groups, reporting the results and the problems encountered during the experiments.

The chapter is organized as follows. Sections 5.2 and 5.3 show my preliminary assessments. Sections 5.4 and 5.5 are dedicated to the experiments I performed with elderly volunteers and the relative problems I had. Section 5.6 is about an Exploratory Data Analysis I performed with the last user group with the aim of extracting some meaningful information from the data. Lastly Section 5.7 is a final discussion on the results I obtained.

5.1 Introduction

The aim of my work is to evaluate the effectiveness of a non-invasive and automatic analysis of the well-being of the elderly in a home-like environment. The experimental results were obtained with the help of young and elderly volunteers¹. Preliminary results were used as a test-bed for my monitoring system and to get feedback on familiarity of the elderly in the use of technology. Taking into account the potentialities and limitations that emerged in these preliminary results, I started to tune the system with young volunteers. Then, I started enrolling elderly volunteers to compare qualitative medical assessments with my automatic data analysis, obtaining encouraging results. My quantitative data analysis was very much in line with the reported medical assessment. Therefore, I enrolled a larger group of healthy

¹All volunteers signed the informed consent to take part in the experiment.

elderly volunteers. On the data acquired with this last group, my experimental analysis was based on a series of correlation tests between the estimated Motility Index and the assessment computed by geriatricians. In this last experiment, I also explored the cognitive evaluation of the subjects through the use of VR games, and I performed additional correlation tests between geriatric assessment and my automatic data analysis. The results I obtained were encouraging even if there are some limitations.

5.2 Preliminary assessment 1: health

Preliminary results were obtained with the help of 5 young volunteers and 5 elderly patients, selected by physicians, recently discharged from the hospital. They spent some days inside the facility alone or in pairs, performing daily living activities and were asked to self-acquire health parameters at least twice a day using the provided medical devices. I use these measures as a test-bed for my monitoring system and to test elder familiarity with technology. During their stay, physicians performed their qualitative evaluations on the patients and I analyzed data coming from the sensors present in the facility.

Health assessment With the goal of evaluating the quality and expressiveness of the obtained data, I first performed an analysis with the health data collected, which were self acquired by patients at least two times per day. I carried out this analysis with the help of a software platform called Rihealthy¹, that allows remote and efficient visualization of patient vital parameter. The data obtained by the health sensors are collected on the RiHealthy platform and can be accessed through a web interface and a mobile application. Figure 5.1 shows the RiHealthy web interface. The main page displays a calendar where the doctor can visualize the measurements taken by the patient (orange squares). Measurements types are represented by different white icons within the squares. By clicking on a square, measurements details are shown: patient, acquisition time, parameter and value. The user can switch between patients using the buttons in the right column, where the contacts of patient caregivers and family members are also included. From the same web interface, the medical user can also prescribe supplementary measurement sessions. The planned time of such session is notified to the patient through a dedicated smart

¹<http://www.tihealthy.com/>

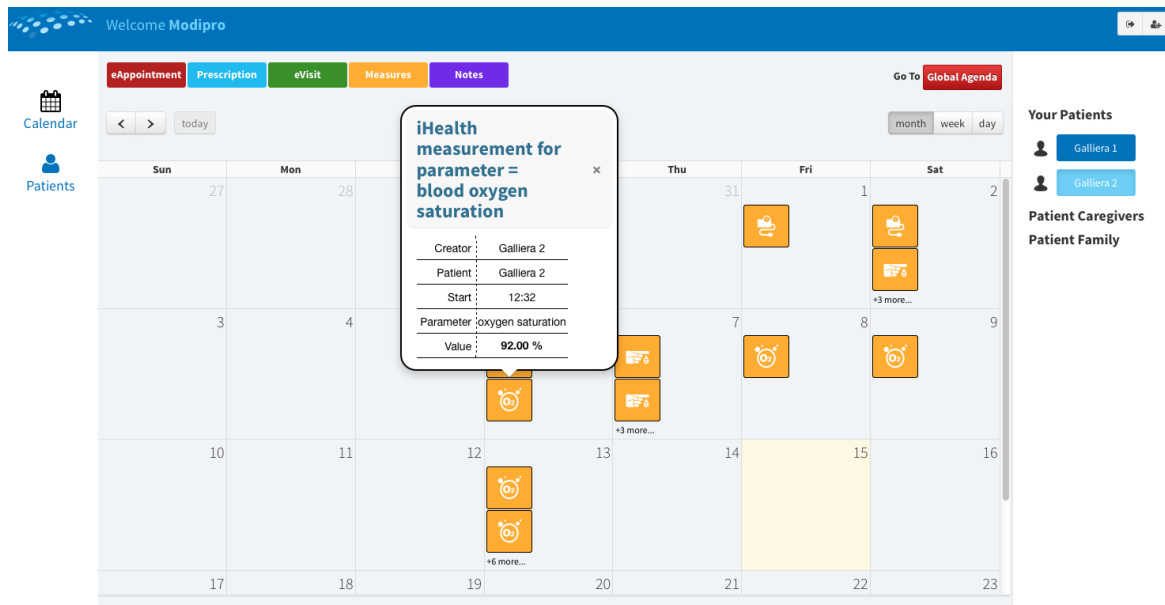


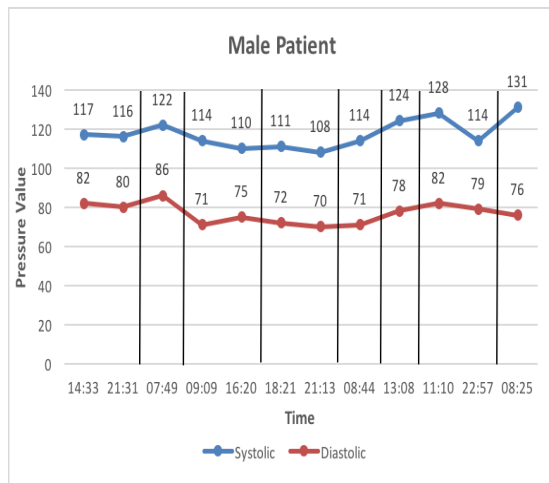
Figure 5.1 RiHealthy platform interface. The monthly calendar shows all the measures for each patient as orange squares. A detail is shown for a blood oxygen saturation measure.

phone app, which is also used to connect to the devices and collect the measurements. The collected measurements can then be checked remotely by the doctor, ensuring the maintenance of standards of care and, at the same time, enabling resource optimization.

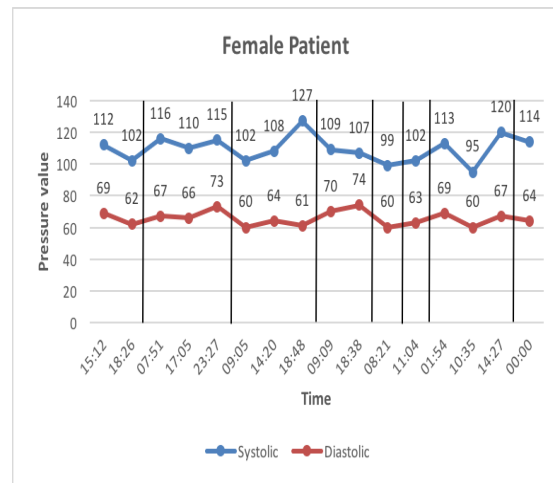
Starting from the collected measures, I analyzed the data, collecting them weekly. This allows to check the state of health of the patients during their stay in the facility. Figure 5.2 shows some examples of the trends on the data acquired from two young volunteers, one male and one female who spent a week in the facility together. Vertical lines in Figure 5.2 represent the change of the day. I reported the trends on Blood Pressure, Oxygen saturation and Weight.

The data visualization tool I identified meets the requirements of physicians. The geriatrics team stressed that for the measurements to be useful in the remote monitoring of patients, they should be taken at least twice a day.

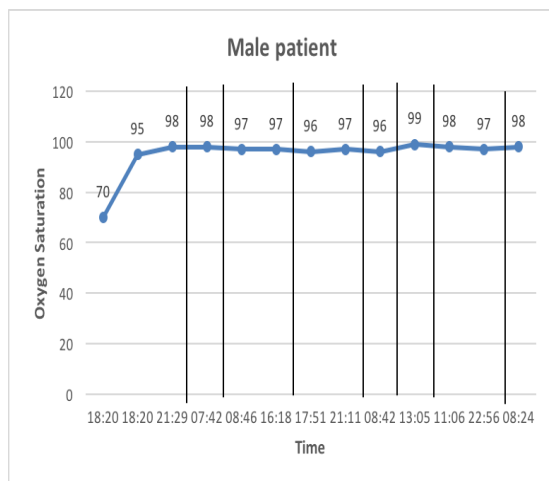
Open problems This preliminary analysis highlighted the first problems, concerning the health measures and the permanence of volunteers inside the facility. From the point of view of the health measures, they have to be acquired twice a day by the patients using the automatic devices and the mobile app. Elderly volunteers did



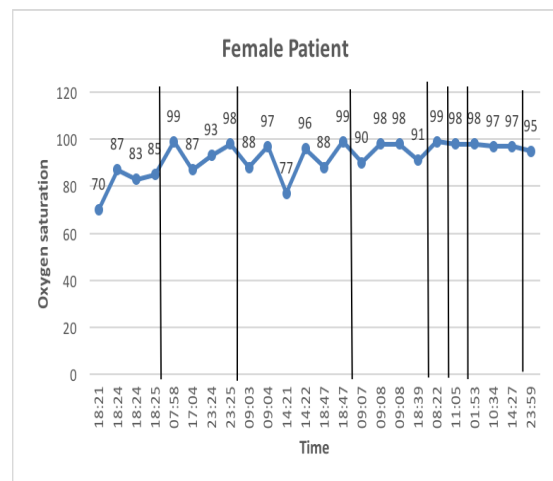
(a) Blood Pressure



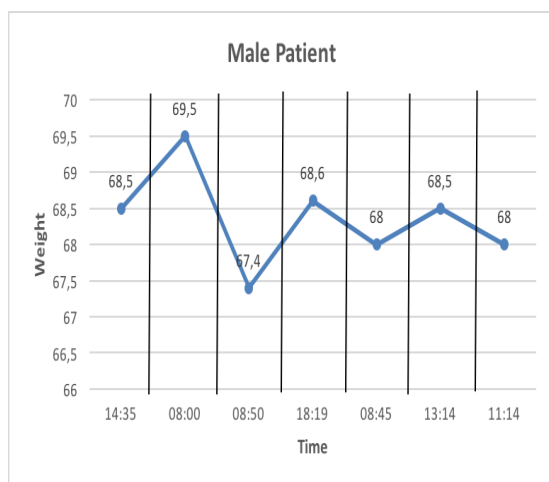
(b) Blood Pressure



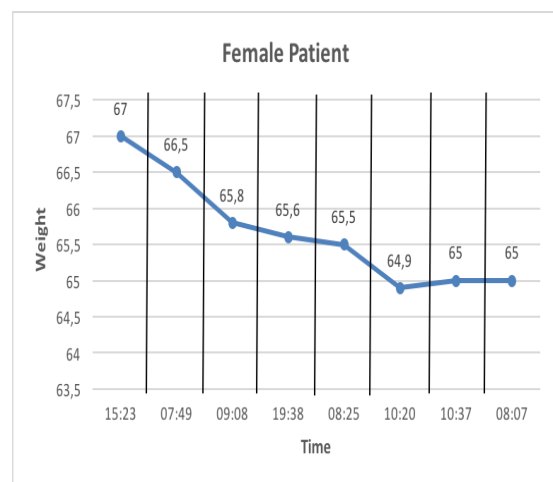
(c) Oxygen Saturation (SPO2)



(d) Oxygen Saturation (SPO2)



(e) Weight



(f) Weight

Figure 5.2 Health data from two young volunteers, one male and one female during a week. Vertical lines indicate the day of the week. (a) Shows male blood pressure records , (b) shows female blood pressure records, (c) shows male SPO2 record, (d) shows female SPO2 records, (e) shows male weight records, (f) shows female weight records.

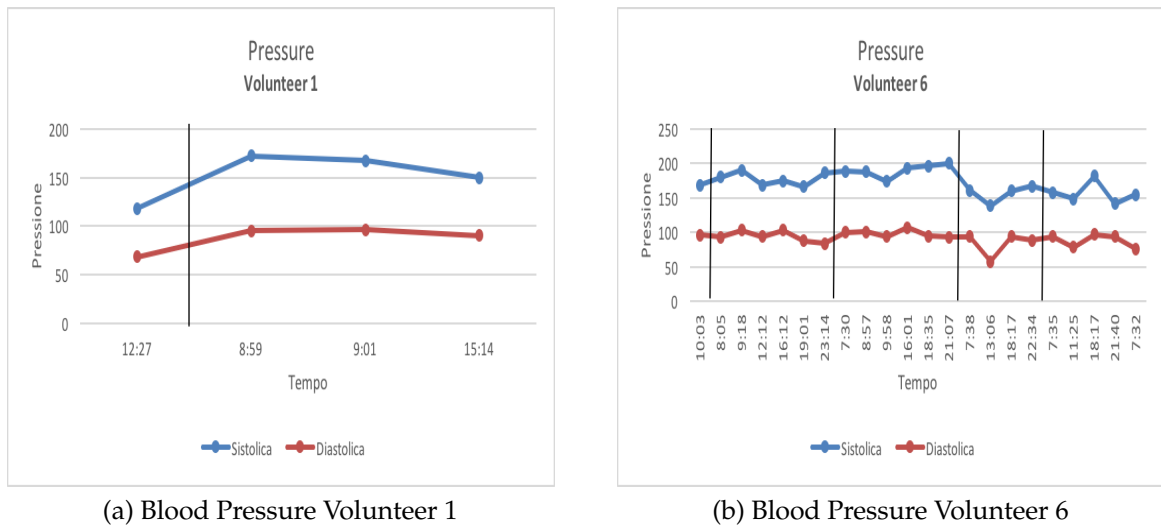


Figure 5.3 Pressure data from two elderly volunteers, one male and one female during a week. Vertical lines indicate the day of the week.

not comply with the provision regarding the number of acquisitions to be made, the main problem was the use of technology. For example Figure 5.3 shows pressure data acquire by elderly volunteers who spent five days in the facility. Notice that volunteer 1 took health measures only for two days while volunteer 6 did more than the measures requested.

Although the mobile app was very simple and intuitive (see Figure 5.4), most of the elderly patients had no confidence with smart phones and had difficulty to unlocking the screen (even if I chose the simplest code possible, Figure 5.4 right), selecting icons, and remembering the various steps needed to record the measures. It often happened that the measurements were recorded manually by the elderly on a piece of paper. For this reason, in the following experiments, the self collection of health data was not included.

The other problem to be considered is related with the permanence of elderly volunteers inside the facility. Despite having signed the informed consent to take part in the experiment, the hospital staff was required to ensure the maximum safety of the volunteers inside the apartment during day and night time. This proved to be a problem, especially during night hours, due to the lack of medical and nursing staff during these hours, resulting in a work overload for the present personnel. Taking into account this problem, in the following experiments, the permanence of volunteers within the facility was limited to daytime hours.

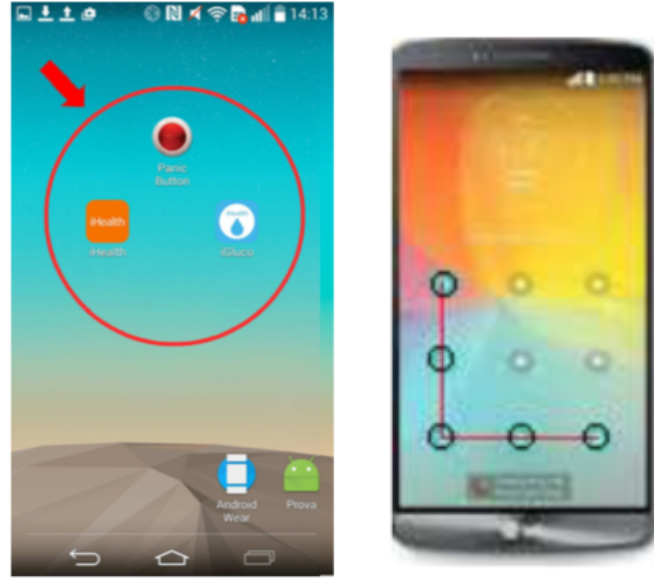


Figure 5.4 Screen shot of the mobile phone home, there are only three icons, one is the emergency call and the other two are the health devices app. On the right is shown the mobile phone unlock code.

5.3 Preliminary assessment 2: motility

In a second experimental session, I assessed the performances of the motility analysis tools. In order to obtain a precise quantitative assessment, I produced a dataset of *manually annotated data*. The annotation was performed by visually inspecting the video sequences acquired by CAM_1 and CAM_2 .

Table 5.1 Summary description of the manually annotated sequences recorded in the monitored apartment. T_{sit} is the Time spent sitting, TS is the Time spent Standing and TM is the Time spent Moving

Sequence	Age	Time interval [min]	T_{sit} [s]	TS [s]	TM [s]
#u1	23	90	478	79	296
#u2	22	150	5260	755	1165
#u3	24	120	224	174	181
#u4	36	30	126	79	384
#u5	40	30	99	77	196

For this first experimental analysis, I considered a user group composed of five young volunteers (3 male and 2 female, mean age 29 ± 7.4) who spent from one to three hours inside the facility alone. In Table 5.1, I summarize the main characteristics of the 5 sequences considered. In each sequence, a single subject was observed while moving without constraints in the apartment and spontaneously performing common daily-life activities (e.g. walking, sitting at the table, standing in front of the kitchen). For these reasons, the acquired data represent a suitable test-bed to tune the system and to evaluate my methods.

I started my analysis computing a manual annotation on the acquired data, then I compared the annotated data with the automatic assessment. Table 5.2 reports a detailed experimental analysis performed on the 5 fully annotated sequences of young volunteers. For each sequence, I report the total amount of time in which a measurement is available, a subset of the statistics mentioned in Section 4.2.3 that are the total time spent sitting, standing and walking. For each measure I reported the ground truth, the estimated values, and the associated relative errors computed in percentage. All quantities are expressed in seconds. It is worth noting that, among the temporal period of observation, the subjects spent a certain amount of time out of the fields of view of the vision sensors (e.g. in the bedroom). It can be also noticed that the performance is in general very accurate (global error less than 10%), also considering that the annotation, manually performed, is affected by an uncertainty itself.

Table 5.2 Quantitative analysis on the motility quantities performed on 5 annotated sequences. GT represent the ground truth, EST is the estimated value and ERR is the associated relative error.

Seq.	Total Time [s]		Sitting Time [s]			Standing Time [s]			Walking Time [s]		
	GT	EST	GT	EST	ERR	GT	EST	ERR	GT	EST	ERR
#u1	5400	853	478	496	3.8%	79	74	6.3%	296	283	4.4%
#u2	9000	7180	5260	5239	0.4%	755	752	0.4%	1165	1189	2.1%
#u3	7200	579	224	202	9.8%	174	164	5.7%	181	213	17.7%
#u4	1800	589	126	128	1.6%	78	84	6.3%	384	377	1.8%
#u5	1800	372	99	92	7.1%	77	81	5.2%	196	167	14.8%

Table 5.3 reports the results on the estimates of the posture – the number of sit-to-stand (TR_{2stand}) and stand-to-sit (TR_{2sit}) – and velocity – the number of still-to-moving (W) and moving-to-still (S) – transitions, which allow us to identify the

Table 5.3 Accuracies on transitions of posture or dynamics, for which I have a ground truth available. Each estimate is coupled with the corresponding ground truth value, and the associated relative error.

Sequence	TR_{2stand}			TR_{2sit}			W			S			#TRACKS		
	GT	EST	ERR	GT	EST	ERR	GT	EST	ERR	GT	EST	ERR	GT	EST	ERR
#u1	10	8	20%	8	8	0%	6	5	16%	13	14	7,7%	30	21	30%
#u2	20	23	13%	21	23	13%	37	38	27%	57	48	15,8%	115	109	5,2%
#u3	5	5	0%	5	5	0%	11	13	18,2%	10	12	20%	22	25	13,6%
#u4	9	10	11%	8	10	25%	9	9	0%	18	14	22,2%	36	30	16,7%
#u5	3	3	0%	3	3	0%	7	7	0%	7	7	0%	15	15	0%

tracks composing the trajectories. A comparison with the ground truth values (in brackets in the table) shows the reliability of my estimates, the global error between my estimate and the ground truth is less then 10%.

In the evaluation protocol designed together with the physicians there are also a number of motility quantities for which a ground truth is either not available or very difficult to be gathered. Such measures are reported in Table 5.4, where the columns refer to the total distance walked (DW), the average distance covered in the tracks (AD), the average velocity of moving tracks (AV), the longest distance covered in a single track (LD), and the longest track (LT). Such results have been positively evaluated with a qualitative comparison with the corresponding video sequences.

Table 5.4 Estimates of statistics for which the ground truth is not available

Sequence	DW [m]	AD [m]	AV [m/s]	LD [m]	LT [s]
#u1	189.1	3.7	0.2	38.3	174
#u2	1123.6	7.2	0.2	157.6	853
#u3	277.2	9.5	0.4	85.5	130
#u4	149.8	2.8	0.2	22.0	56
#u5	99.4	3.8	0.2	15.4	33

It is worth noting that the capability of appropriately quantify the level of dynamism of a subject is of high relevance in this application domain, also considering that elderly people are characterized by a range of walking speeds which is in general lower than for younger adults. I thus provide a simple example showing the

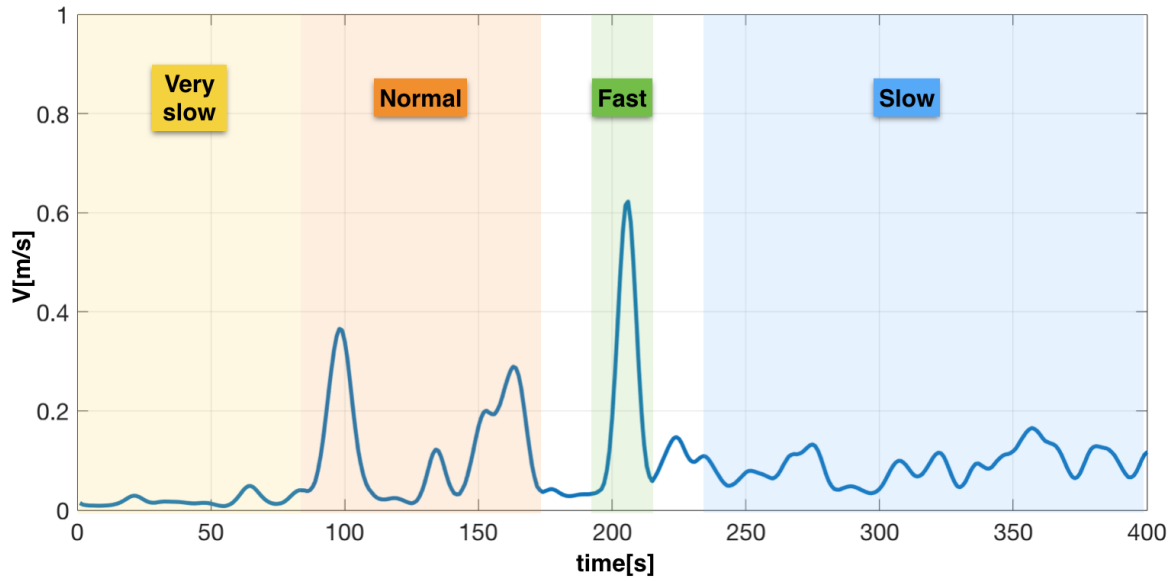


Figure 5.5 The velocity estimated over time on a sequence where a subject walks at different speeds.

possibility of further analyzing the data considering more subtle dynamic properties. In particular, Figure 5.5 shows the velocity magnitude in a specific sequence where the volunteer was asked to move at different velocities in the apartment. Notice that the velocity values for normal walking are comparable to the estimates on the average velocity reported in Table 5.4.

I finally provide in Table 5.5 the Motility Index estimations for the five subjects, according to Eq. 4.11. Together with the final MI , in the table I also report the values of the two main terms of the equation, namely the inactivity time which equals to the percentage of time spent sitting or standing still, and an estimation of activity represented by the number of postural or dynamic transitions over the entire period. The values of the parameters α and C have been empirically estimated and set to 0.2 and 10, respectively.

It can be easily observed that the MI values tend to increase as the amount of inactivity increases as well, speaking in favor of the reliability of our estimate. We can notice, for instance, in sequence #u2 the volunteer spent most of the time sitting (about the 83% of the total time of observation) and this corresponds to a high value of MI . Conversely, the dynamism of subject for sequence #u4 is richer, thus the Motility Index is much lower (notice that MI takes values between 0 and 1, approaching 1 when the motility of the subject is not satisfactory).

Table 5.5 Motility Index (*MI*) for the 5 subjects (see text for details).

Sequence	% Inactivity Time	Inactivity from transitions	MI
#u1	0.67	0.57	0.65
#u2	0.83	0.81	0.83
#u3	0.63	0.46	0.60
#u4	0.36	0.25	0.34
#u5	0.47	0.46	0.46

I conclude observing that this analysis has been performed on a set of manually annotated data of volunteers in order to provide a quantitative evaluation of the approach. In the experiments described in the next section *MI* is estimated on a larger variety of volunteers.

Open problems The results I obtained in this first experiment are very encouraging, regarding the accuracy of the methods in estimating various motility quantities. This first user group was composed of young volunteers. It was useful to tune the system, but not scientifically significant because of the gap in the age of the volunteers with respect to the age of the real end users. In the next experiment, I will introduce elderly volunteers to have more significant results. The experimental assessment I carried out in my work suffers from a technical limitation. As mentioned before, volunteers agreed to spend some hours in the facility, and this allowed us to evaluate some aspects of visual data analysis. Instead, to allow machine learning algorithms to infer complex activities and habits of the subject and to evaluate the overall well-being, the person should spend some days in the apartment as originally planned. This was not possible for safety reasons, and as a consequence instead on personalized models of behavior analysis, I focused on a more general model for motility assessment (the so called, Motility Index). In any case, motility is a crucial aspect in the evaluation of the frailty of elderly subjects. My formulation of the Motility Index, following the suggestion of physicians, would enrich and complement the qualitative evaluation of frailty through the MPI.

Another issue which is worth mentioning at this point is that the computational models I describe in my work have some limitations in terms of data association. That is, they work more reliably in the presence of one person at the time in a scene.

Table 5.6 Geriatric assessment on elderly volunteers. The table reports all the measures that contribute to the formulation of the Multidimensional Prognostic Index (MPI) and the MPI itself. In particular, I reported the Short-Portable Mental Status Questionnaire (SPMSQ), the Exton-Smith Scale (ESS), the Activities of Daily Living (ADL), the Instrumental Activities of Daily Living (IADL), the Mini Nutritional Assessment (MNA), the number of drugs (Med.), the Cumulative Index Rating Scale (CIRS) and the Short Physical Performance Battery (SPPB).

ID	Gender	Age	SPMSQ	ESS	ADL	IADL	MNA	Med.	CIRS	SPPB	MPI
#v1	M	68	10	20	6	8	14	3	1	11	0,063
#v2	M	71	10	20	6	8	13	1	1	11	0,063
#v3	M	66	10	20	6	8	14	1	3	10	0,125
#v4	F	78	10	20	6	8	14	6	5	10	0,188
#v5	F	79	10	20	6	8	14	1	3	7	0,125

For this reason, all my experiments of the following sections have been carried out by requiring the presence of one person only in the room. To solve this issue we could easily adopt a complementary wearable sensor, such as the Eliko (see Section 3.2.3) and solve the data association problem with the help of multi-modal information. This technical challenge will be the objective of future work.

5.4 Experiment 3: coherence of geriatric assessment and automatic assessment

The experimental results comparing the geriatric assessment and the automatic analysis are based on a group of 5 healthy elderly volunteers (3 male and 2 female, mean age 72.4 ± 5.2) who spent two hours each inside the facility alone. During their stay, clinical test were performed by physicians and data were collected and manually analyzed. The geriatric evaluation was performed inside the facility in order to allow a direct comparison between qualitative and automatic analysis. Once they finished the tests, the volunteers spent some time alone, during which the algorithms gathered data to estimate the motility quantities used to obtain the Motility Index. Table 5.6 shows the results obtained from the qualitative analysis, MPI and all the variables involved in its formulation.

The results that incorporates both the geriatric assessment and the manual annotation (ground truth) of the data are summarised in Table 5.7.

Table 5.8 reports an analysis on the set of data acquired with elderly healthy patients. We first observe how my estimate, in percentage, of the amount of time

Table 5.7 Evaluation of 5 elderly subjects in good health: summary of the geriatric assessment, in terms of gait speed measured during the test of a 4 meters walk. The last three columns report a coarse manual annotation carried out by the author by visually inspecting video sequences.

ID	Gender	Measured Gait Speed [m/s]	% STILL	% SIT	% MOVING
#v1	M	1.299	20	54	26
#v2	M	1.026	15	71	14
#v3	M	1.556	26	50	24
#v4	F	0.875	19	62	19
#v5	F	1.084	4	89	7

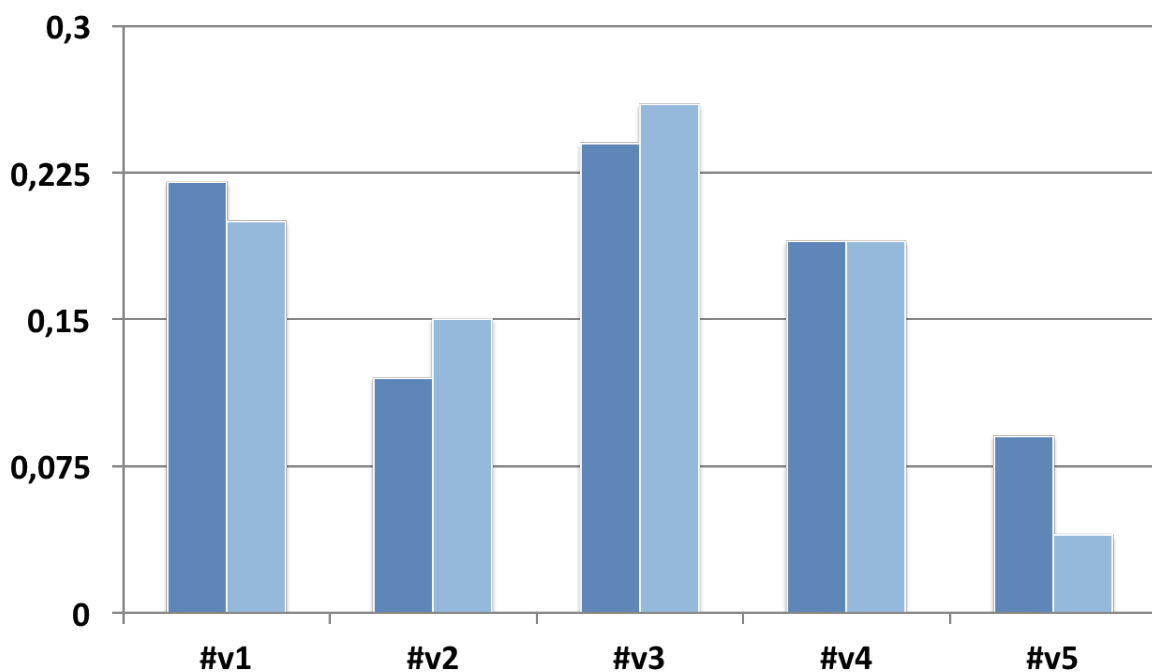


Figure 5.6 Comparison between manual annotation shown in table 5.7 (light blue) and automatic (dark blue) assessment shown in table 5.8 in terms of percentage of time spent standing still.

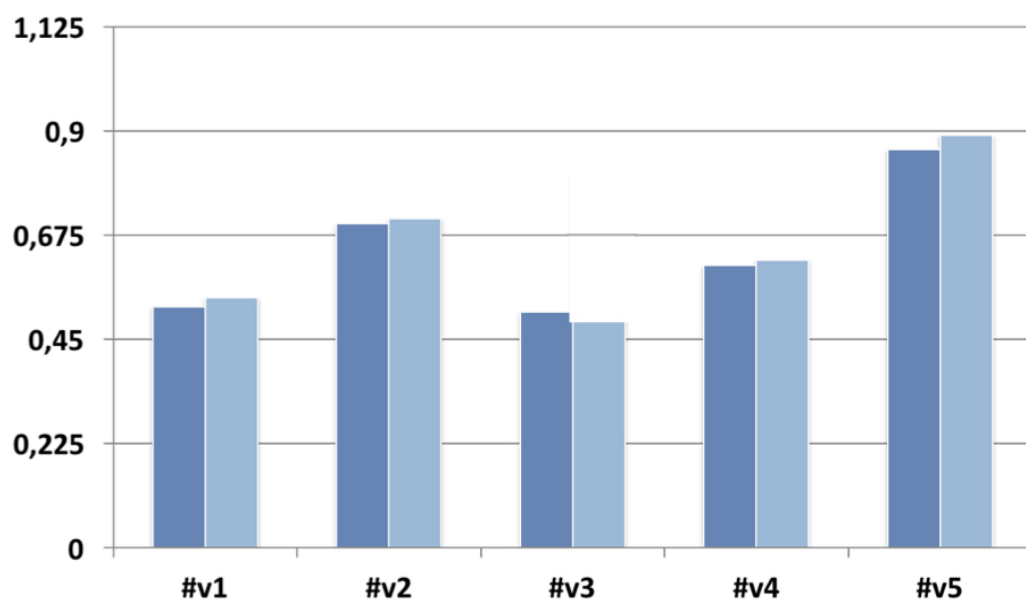


Figure 5.7 Comparison between manual annotation shown in table 5.7 (light blue) and automatic (dark blue) assessment shown in table 5.8 in terms of percentage of time spent sitting.

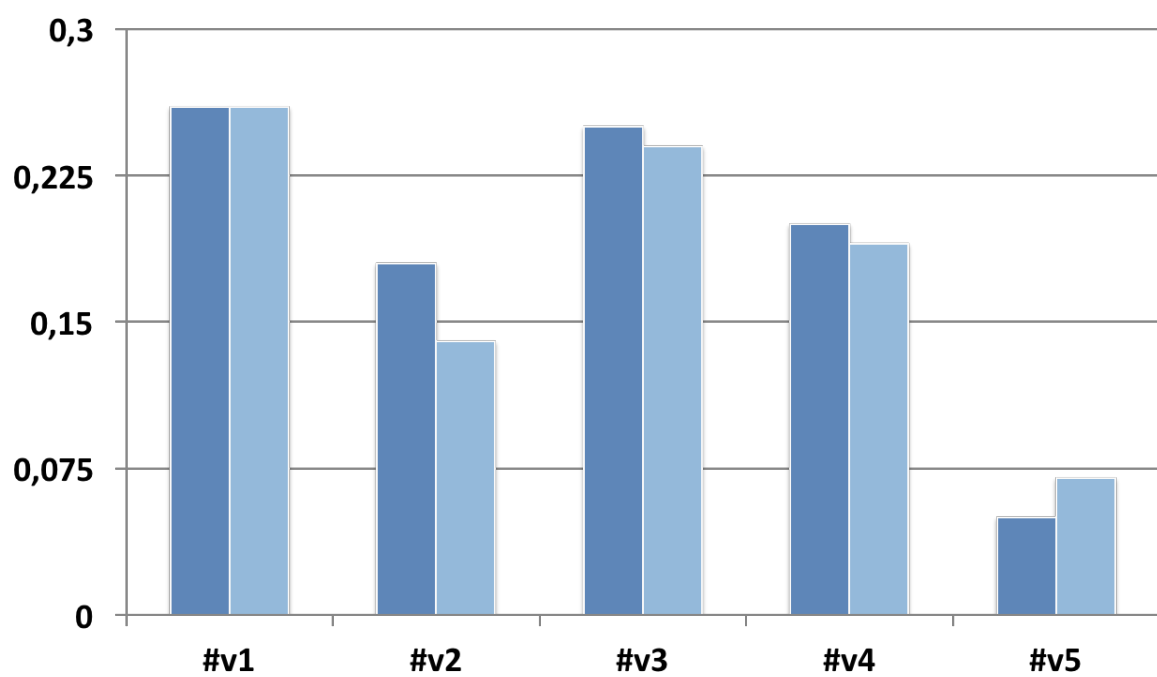


Figure 5.8 Comparison between manual annotation shown in table 5.7 (light blue) and automatic (dark blue) assessment shown in table 5.8 in terms of percentage of time spent moving.

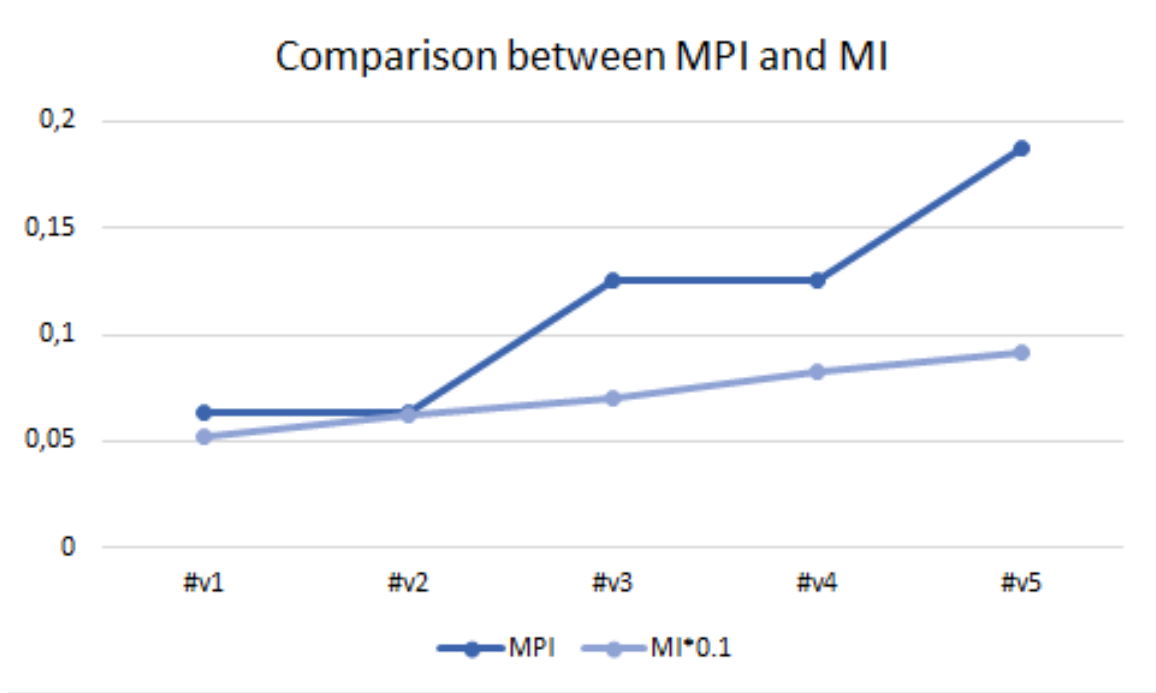


Figure 5.9 Comparison between MPI and MI on the five healthy elder volunteers. Automatic evaluation MI produces a result that is very much in line with the qualitative MPI.

spent by patients in standing (Figure 5.6), sitting (Figure 5.7), moving (Figure 5.8) state is very coherent with the manual annotation shown in Table 5.7. We can also notice that my estimated average speed, albeit difficult to compare with the speed estimated by geriatricians in a single walk, produces the same relative ordering among volunteers. Lastly, the Motility Index produces a result which is very much in line with the reported MPI: in particular, the healthier volunteer is #v1, the weaker is #v5, see Figure 5.9. From this analysis, it appears that the *MI* could effectively complement and enrich the *MPI* estimation.

Figures 5.10 and 5.11 report for each volunteer the details on some of the estimated motility quantities carried out on the elderly volunteer data. Figure 5.10 shows the average number of state transitions (TR_{2sit} , from stand to sit and TR_{2st} from sit to stand) and the number of walk instances in the observed time span. Figure 5.11 reports for each subject the longest walk distance and the longest walk time: here in particular we notice how #v1 walks faster and spans longer distances than other subjects, confirming the conclusions obtained from the Motility Index.

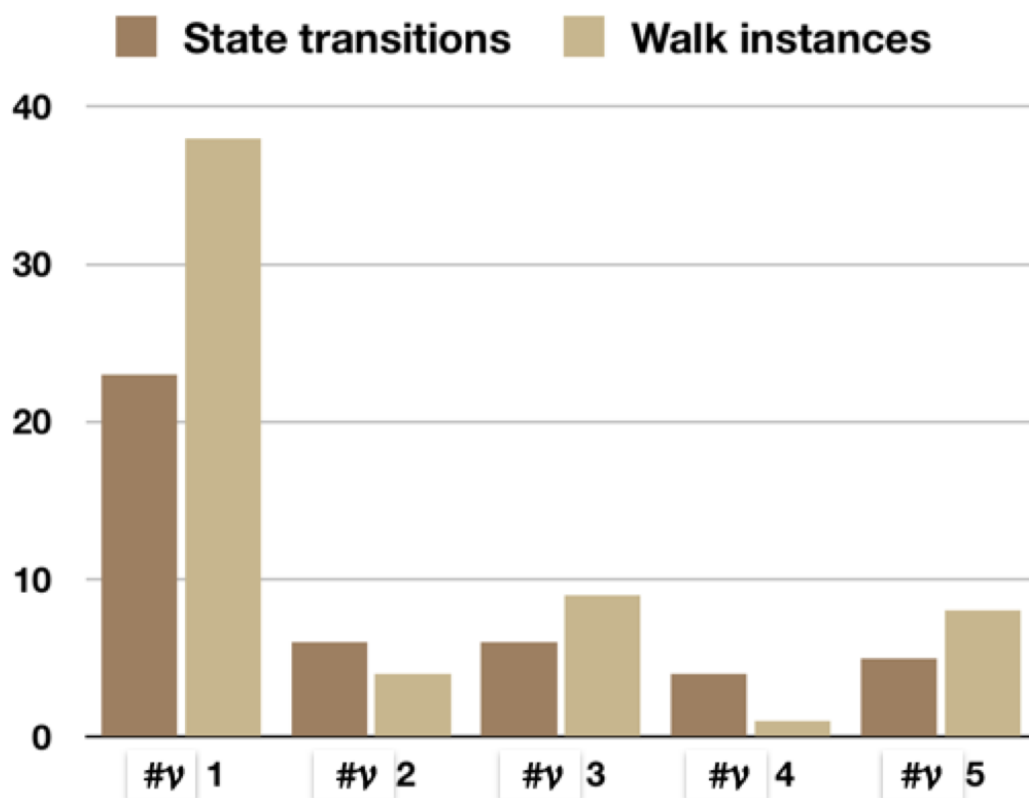


Figure 5.10 Number of state transitions evaluated as the average of TR_{2sit} and TR_{2st} and walk instances W for each volunteer (#v1 to #v5).

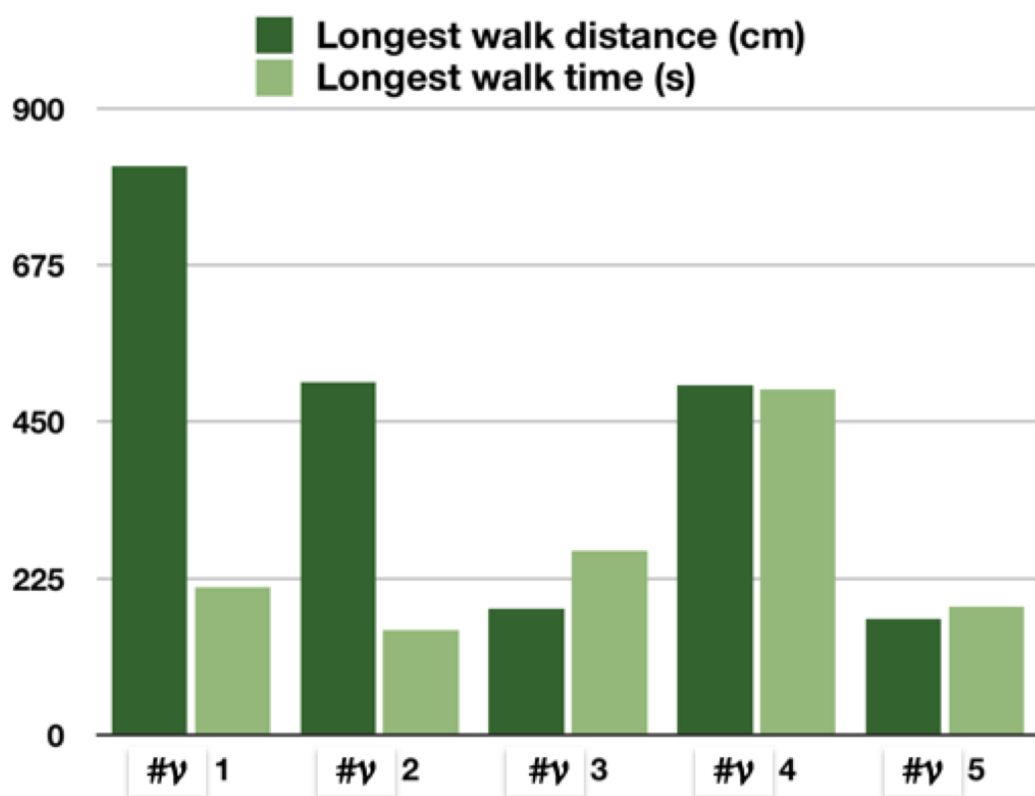


Figure 5.11 Longest walk distance and walk time for each volunteer (#v1 to #v5).

Table 5.8 Automatic evaluation of 5 elderly subjects in good health: the observation time, the estimated percentage of time spent standing still, sitting, or walking, the estimated average speed, and the overall estimated Motility Index (MI).

ID	% STILL	% SIT	% MOVING	Avg. Velocity	MI
#v1	22	52	26	0.39 ± 0.21	0.52
#v2	12	70	18	0.27 ± 0.19	0.62
#v3	24	51	25	0.31 ± 0.21	0.70
#v4	19	61	20	0.19 ± 0.12	0.82
#v5	9	86	5	0.26 ± 0.18	0.91

5.5 Experiment 4: analyzing a larger group of active and healthy aging volunteers

Motility assessment The last experiment I carried out is an analysis on the proposed techniques with a larger group of volunteers, 24 (10 male and 14 female, mean age 72.7 ± 5.4) who spent 2 hours in the facility.

All volunteers were active and healthy aging over 65 years old, with $MPI \leq 0.25$. During their stay, volunteers were first interviewed by geriatricians, who estimated standard frailty tests and computed the Multidimensional Prognostic Index (MPI) (Pilotto et al., 2008), Short Physical Performance Battery (SPPB), and the Time Up and Go test (TUG). Then, the volunteers carried out the VR-based cognitive test which will be described below. After that, they spent at most two hours in the facility, free to move, relax, read or watch TV, have a snack or a drink.

In this case, the statistical analysis I performed, assesses the correlation between the manual reports provided by physicians and the automatic analysis obtained by my data analysis algorithms.

In particular, my experimental analysis is based on a series of correlation tests between the estimated MI and the indices computed by geriatricians in their standard daily practice. Preliminary correlation results were discouraging, then I performed a closer analysis on the quality of available data. Figure 5.12 shows the cumulative values of the Spearman correlation between SPPB and MI and confidence of volunteers ordered by observation duration (from the longest to the shortest) excluding stays shorter than twenty minutes. It highlights how the correlation decreases, but the overall correlation is steadily > 0.7 . For durations shorter than twenty minutes the correlation significantly drops. The reason for this is motivated by a simple

empirical consideration — to behave in a natural way the volunteer needs some time to adjust to the unknown environment. Thus we carried out a statistical analysis on observations longer than twenty minutes, and obtained the following results:

- *MI* and SPPB: Spearman coefficient = 0.85 p-val = 0.09
- *MI* and hand grip strength: Spearman coefficient = 0.417, p-val = 0.14
- *MI* and MPI: Spearman coefficient = 0.26 p-val = 0.18

We notice a very high correlation between my Motility Index and the aggregate measurement SPPB; we also notice a significant correlation with one specific dimension (hand grip strength). We also observe a low correlation with MPI; this is not surprising, since MPI incorporates a wider class of dimensions which are not directly related with motility like the Mini Nutritional Assessment (MNA) and the Cumulative Illness Rating Scale (CIRS).

It is more difficult to assess the reliability of our estimated velocities, as they are computed over a very heterogeneous and highly subjective set of activities, while the ones carried out by physicians are clearly associated with a specific request (e.g., walk along a line from a starting point to an end point). I report a correlation coefficient between the velocity associated with the TUG test and my estimated average velocity of about 0.71, p-val = 0.07.

The obtained results confirm that automatic measurements are meaningful, and well correlated with the medical tests, and can thus be used to assess motility between the sporadic medical evaluations.

VR-based cognitive assessment In this last experimental assessment, a complementary analysis of the cognitive status was also carried out.

In order to understand whether the VR game can be successfully used for the cognitive assessment of patients, I conducted a set of experiments with a subset of 6 elderly volunteers from the final experiment (see Section 5.4) (ages 72.8 ± 5.8). Before starting the evaluation of cognitive assessment using the developed system, a doctor filled out the Short Portable Mental Status Questionnaire (SPMQ) (see Section 2.2.2), and the General Practitioner Cognitive Assessment of Cognition (GPCog) a cognitive impairment screening test (Brodaty et al., 2002). The final scores of SPMQ and GPCog were used in order to understand whether a useful correlation with the scores provide by the automatic system exists.

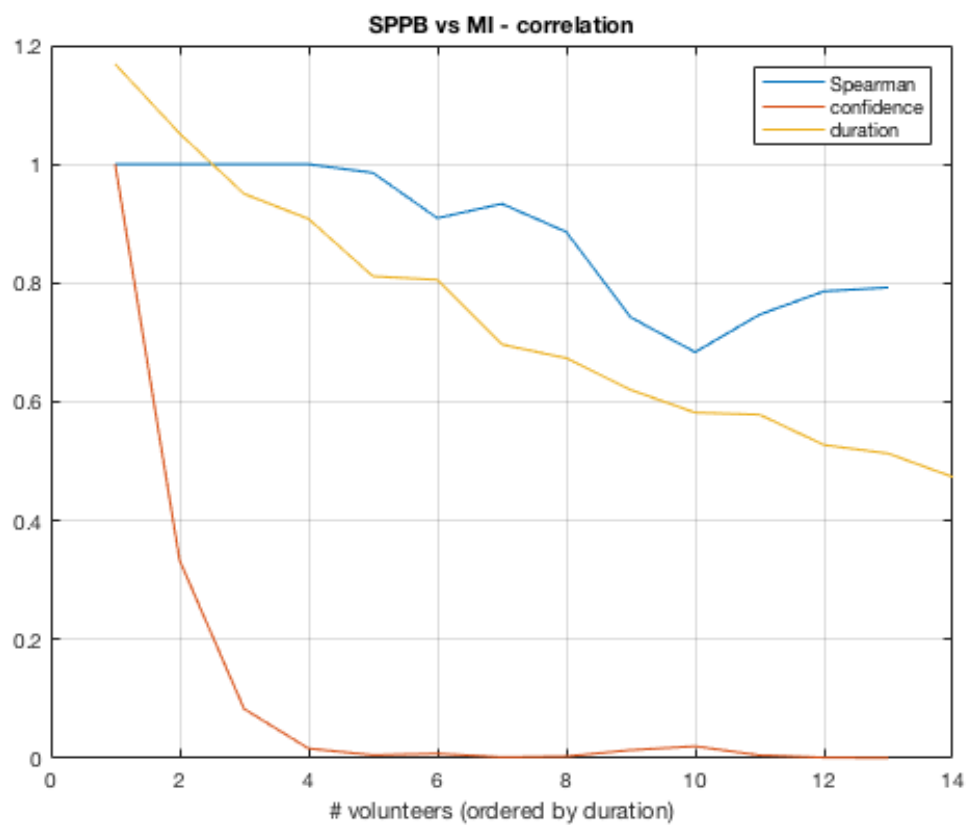


Figure 5.12 Cumulative analysis on the correlation between SPPB and MI on subsets of volunteers ordered by duration (duration is expressed in hours - e.g. 1 is 1 hour). See text for more details on how the plot is constructed

The developed system, (see Section 3.2.2), allows us to store the following data:

- Given an actual shopping list, i.e., the list is randomly generated and provided to the user, and it is compared with the shopping cart he/she effectively composes.
- List of errors in the “shopping task”, i.e., number and typology of errors: wrong items put in the shopping cart, numbers of item deleted and/or reinserted in the shopping cart.
- List of errors in the “payment task”, i.e., whether the payed amount of money is wrong.
- List of errors in the “recall task”, i.e., the number of items in the shopping list that are not correctly remembered after having completed the task.
- Partial time spent to complete the given tasks.

The performance of the patients with the proposed VR-based cognitive assessment has been evaluated through several parameters. The ShoppingScore (SS) takes into account the number of bought items that actually are (CI) and are not (WI) in the list and also the number of items deleted from the cart (DI). SS can vary between 0 and 10 and it is obtained according to the following equation:

$$SS = CI - \alpha WI - \beta DI$$

Different weights (α and β) are associated with different errors: if a patient selects an incorrect item, it is a mistake, but if he/she realizes it and corrects it he/she will be less penalized.

The PaymentScore (PS) is set to 0 if the payed amount is incorrect and 10 if it is correct. Otherwise it is computed, taking into account the number of times the patient has reset the payment task, which is considered an error (E), and γ is an empirical constant (fixed at 0.5 in this experiment) as:

$$PS = 10 - \gamma E$$

	GPCog
Shopping Score	0,57 *
Shopping Time	0,62 *
Payment Score	0,59 *
Payment Time	0,84 **
Remembered Items	0,78 **

Table 5.9 Pearson correlation coefficients among the parameter computed by the "Supermarket" test and the GPCog results. * $p < 0,05$; ** $p < 0,001$

In both cases, a low score can be related to an impairment in solving the task, and a high score means that the user completed it easily. Another evaluated parameter is the number of remembered items (RememberedItems): at the end of the game the subject was asked to write down all the items he/she remember he/she had bought. A manual comparison with the correct item list is performed by the physician. Moreover we compute the time to complete the shopping task (ShoppingTime) and the payments task (PaymentTime).

I then computed the Pearson correlation coefficient among the scores computed with the proposed VR game and the GPCog test. Results are reported in Table 5.9.

The GPCog test has an moderate correlation with the parameters ShoppingScore, PaymentScore, ShoppingTime, and a high correlation with PaymentTime and RememberedItems.

Open problems. The main problem I encountered during this stage of my work, was the limitation in the amount of time the elderly volunteers could spend in the facility. From my experimental analysis, it is clear that we need more than 2 hours of data to obtain results that are meaningful and statistically relevant. Also, multiple sessions involving the same volunteer would be useful to assess the potential of my analysis in detecting signs of deterioration. Along the same lines, my experimental analysis lacked an evaluation of the methods with more frail patients. This is also due to safety reasons. All these limitations may be attenuated in future steps of the MoDiPro project, when a new experimental session with volunteering patients staying in the facility will start. So far, I performed a global analysis on the entire observation span of a given patient. Considering the limited amount of data I had to resort to *hand crafted measurements* describing overall motility qualities. When

patients are allowed in the facility for multiple days as originally planned, we will be able to gather a larger amount of heterogeneous data (including health, motility, and ADL) and build data driven statistical tools able to learn and adapt to patients habits and peculiarities. In this way we will also be able to automatically identify deviations from normality and promptly alert the physician.

5.6 Exploratory Data Analysis (EDA)

As a conclusive experimental activity, I report a final work on the feasibility of carrying out an Exploratory Data Analysis (EDA) for my data. Exploring and visualizing the collected measures is an insightful starting point for every analytical process. When it is necessary to extract meaningful information from collections of complex and possibly high-dimensional measures, a preliminary Exploratory Data Analysis is not only a good practice but also a fundamental step before further and deeper investigations can take place. EDA will be a valuable tool in the near future of the project, when a larger amount of data will be available. In this final proof-of-concept I considered the raw data (3D streams obtained from RGBD sensors, one stream per patient) previously gathered during Experiment 3, (see Section 5.5). Instead of summarizing all the visual information in a relatively small set of pre-defined hand crafted measurements, I carried out a simple data processing where a single stream has been partitioned into shorter tracks corresponding to different events of interest — namely *sitting*, *standing*, *walking*. In this way I obtained a higher dimensional variable length feature vector associated with each volunteer. I then mapped such a vector to a fixed size 3D histogram counting occurrences of tracks associated with a given *(space, time)* span. In my analysis I considered different binning choices and later fixed the size of these histograms to a binning equal to twenty. Figures 5.13, 5.14 and 5.15 show histogram depicting different patients, one characterized by slow speed of walking, a rapid one and one that spent most of the time still, respectively.

Then, I explored the set of data with the goal of identifying clusters or internal structures. For this purpose I used ADENINE¹, a command-line Python tool for data exploration and visualization that, combining different EDA methods, creates textual and graphical analytical reports of large scale, data collections. ADENINE is developed with the aim of speeding-up EDAs on large biomedical data collections,

¹<https://github.com/slipguru/adenine.git>

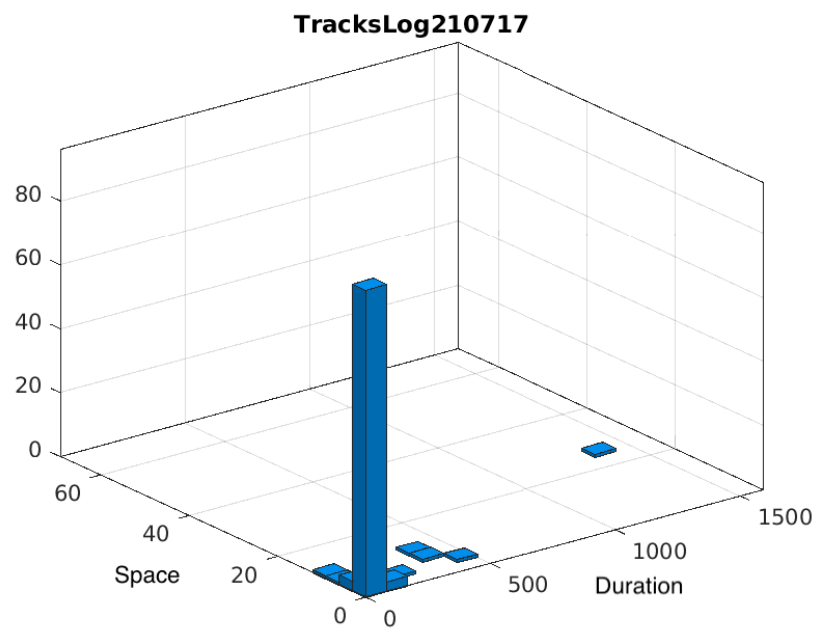


Figure 5.13 Histogram depicting a slow patient

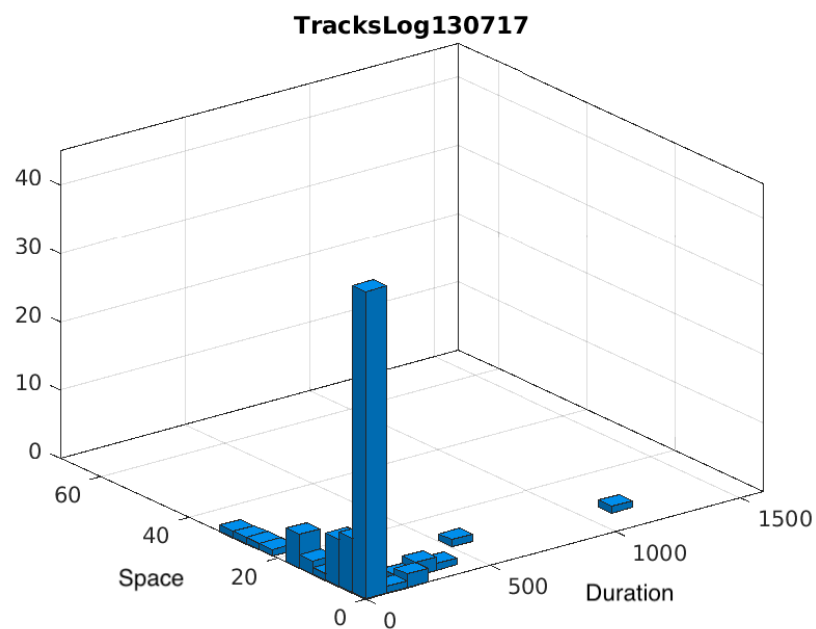


Figure 5.14 Histogram depicting a rapid patient

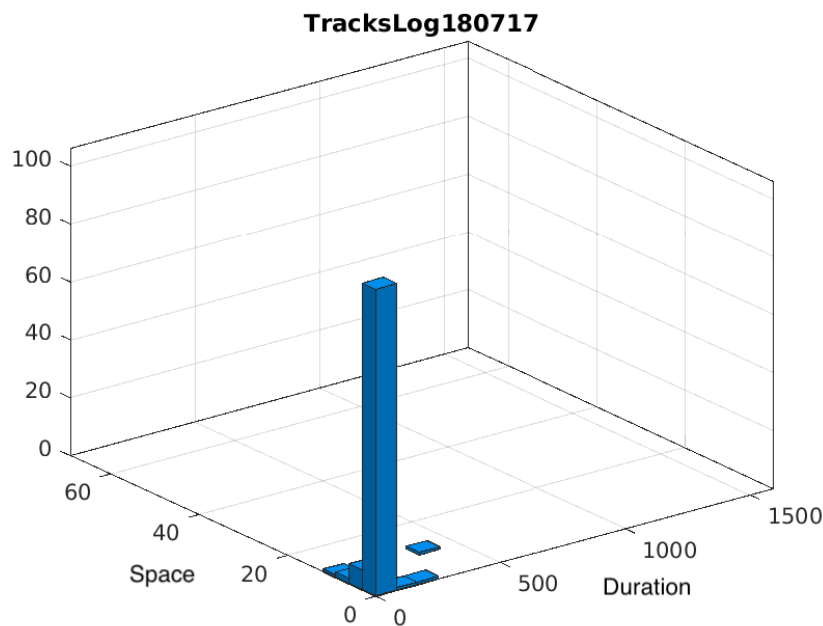


Figure 5.15 Histograms depicting a patient that spent most of the time still.

but it is also appropriate for my case. The data analyst is required to specify the input data and to select the desired blocks. ADENINE, then, takes care of generating and running the pipelines obtained by all possible combinations of the selected blocks. ADENINE includes a set of linear and nonlinear dimensionality reduction and manifold learning algorithms that are particularly suited for projection and visualization of high-dimensional data. I focused on two of the available EDA methods: Principal Component Analysis and t-Distributed Stochastic Neighbor Embedding.

Principal Component Analysis (PCA) (Jolliffe, 2005) is probably the most popular dimensionality reduction technique, and for this reason I included it in my analysis. PCA is typically defined as linear projection of the data onto a lower dimensional space where the variance is maximized. It is used to select a subset of variables from a larger set, based on which original variables have the highest correlations with the principal component. The main goal of a PCA analysis is to identify patterns in data; it aims to detect the correlation between variables.

t-Distributed Stochastic Neighbor Embedding (t-SNE) (Maaten and Hinton, 2008) is a relatively recently proposed nonlinear dimensionality reduction technique specifically developed for high-dimensional data visualization. t-SNE aims at learning a

low-dimensional data projection that reflects the original data similarities as much as possible. The algorithm has two main steps. At first t-SNE devises pairwise probability distributions over high-dimensional samples such that the similar ones are picked together with high probability. Then, the algorithm defines another probability distribution on a low-dimensional map identified by minimizing the Kullback–Leibler divergence between the two distributions. The minimization problem is solved by gradient descent.

Figures 5.16 and 5.17 show two plots obtained with ADENINE by applying PCA and tSNE to the 3D histograms of the 24 active and healthy aging volunteers that joined the experimental campaign reported in Section 5.5. In both cases data are reduced to a 3 dimensional subspace which is easy to visualize. Figure 5.16 identifies a rather compact dominant cluster, which indicates how all patients had a similar behavior and possibly similar motility habits, with one exception. The latter, at a visual inspection of the raw data, is a patient who spent a small amount of time in the monitoring area. Figure 5.17 shows a tighter cluster with three elements deviating from it; they correspond to volunteers deviating from a common behavior, e.g. spending almost all the time sitting on a sofa. Considering the limited amount of data available our EDA is rather simple, but ADENINE appears to be a valuable tool which may complement or guide data analysis in the future steps of the project.

5.7 Overcoming the issues

At the beginning of the project, the aim was to evaluate the frailty of elderly patients over a few days (at least five). I performed a preliminary assessment with the help of some young volunteers and elderly patients as a test-bed for the monitoring system. This preliminary assessment highlighted the first problems. The observational time was the first and the main problem I encountered during my work. This was due to the fact that, since the facility is located within the hospital walls, during the night hours safety requirements imposed by hospital regulation were not guaranteed. Although the geriatric ward was located only three floors away from the apartment, during the night-time, medical staff had no possibility to leave their location, even for emergency. As a result, during the course of my project, I had to organize the experiments in order to overcome this problem, thus enrolling volunteers inside the apartment for a few hours during daytime. As a consequence, I also had to give up the acquisition of medical parameters for the short observational time, and for the

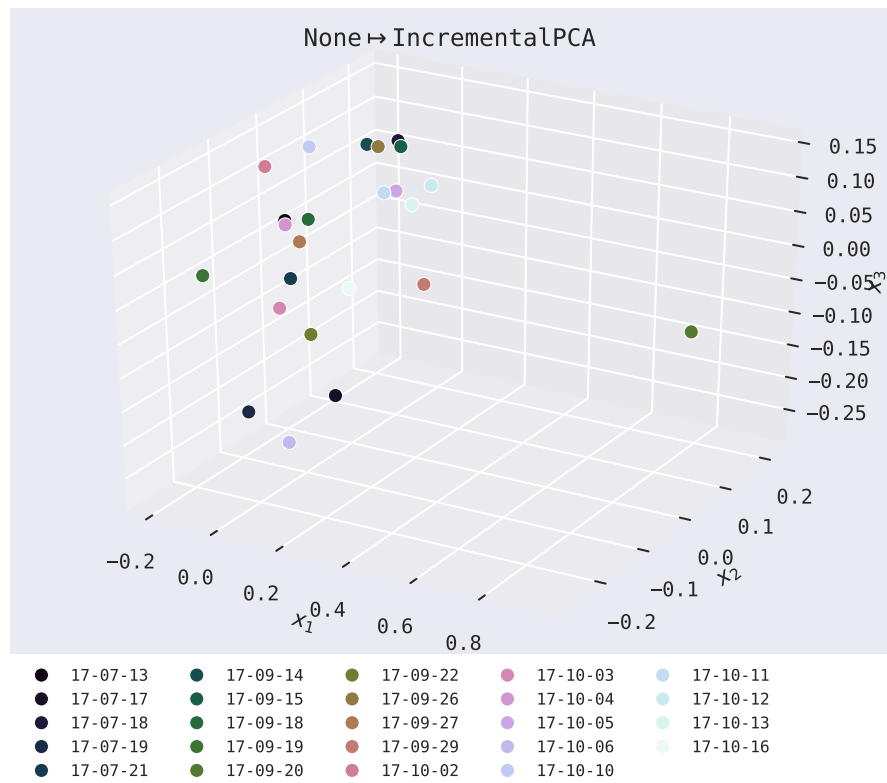


Figure 5.16 PCA performed with ADENINE on the data of 24 healthy elder volunteers (Experiment 3). Each patient is associated with the date he/she visited the facility and with a random color coding. PCA analysis allowed us to identify one person whose habits deviate from common behavior.

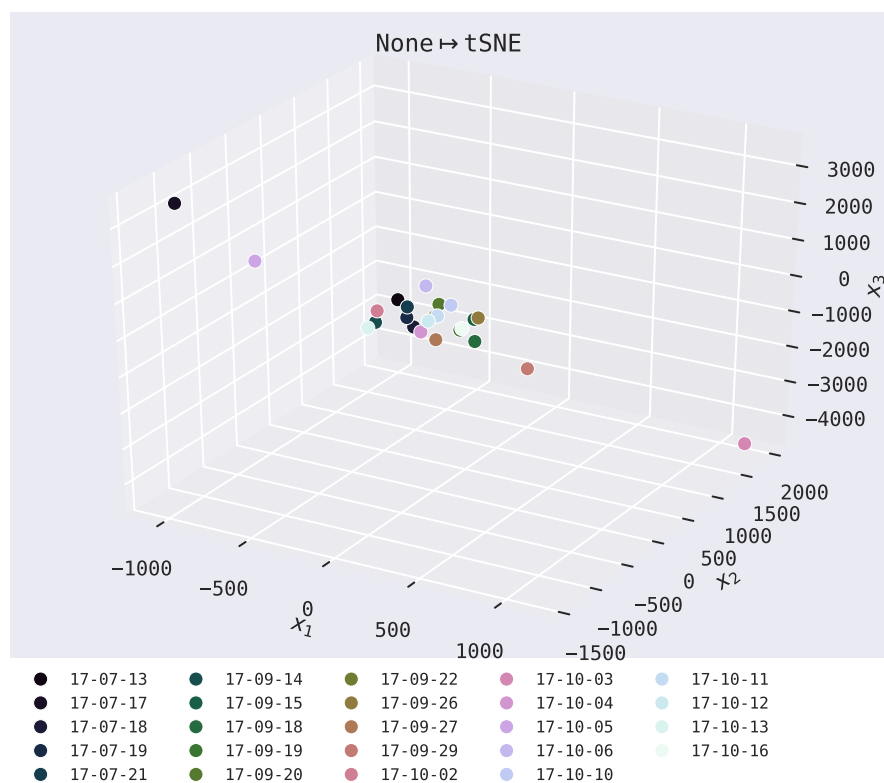


Figure 5.17 t-SNE performed with ADENINE on the data of 24 healthy elder volunteers(Experiment 3). Each patient is associated with the date he/she visited the facility and with a random color coding. t-SNE analysis allowed us to identify a set of data carrying a reduced amount of information with respect to the other.

difficulties in the use of technology encountered with elderly patients. Next, I tuned the system with a new user group of young volunteers. these experiments lead to encouraging results because of the accordance of my automatic motility assessment and the qualitative one performed by physicians. Thanks to the results obtained, I acquired data from elderly volunteers in order to find coherence between medical and automatic assessment of elderly motility. The results of the automatic motility assessment were very much in line with the geriatrics ones.

Finally, I acquired data from a larger number of elderly volunteers. To make my experiments as real as possible, I asked the volunteers to perform some tasks, for example preparing a small snack, walking around the apartment and read a book. The results I obtained are very promising, despite the fact that the evaluation time was shorter than expected. In particular, my automatic analysis led to results in accordance with the qualitative assessment performed by the physicians, nicely showing the potential capability of my approach to complement current protocols of evaluation.

Chapter 6

Conclusion and future works

In this chapter I will summarize the important aspects of my work, setting the stage for future work in this field. In particular, in Section 6.1 I will show my main contribution, in Section 6.2 I will comment on the open challenges that motivate the realization of my project. I will also mention future works in Section 6.3.

6.1 Main contribution

In this thesis, I presented a model for a protected discharge facility which has been designed, implemented, and validated within the Galliera Hospital (Genova Italy). Here the patient, after being discharged from the hospital, may be hosted for a short stay (about one week) and can be monitored by a system of sensors, while physicians and nurses have the opportunity of monitoring him or her remotely. The main goal of my project was first to study how advanced technologies may enable elderly patients to improve their lifestyle and habits, in order to reduce the need for assistance by medical staff, and thus the expenses for both the healthcare public sector and patients. Second, from the data analysis view point, my main challenge was to evaluate the status of the patients, based on very short observations with respect to long observations usually exploited in the literature (6-12 months) (Scanail et al., 2006). For this reason, in close collaboration with geriatricians and domain experts, I identified a set of meaningful measurements that allow us to derive an estimate of a *motility index* to be associated with the patient's overall health status. Today, the model hosts a variety of sensors and runs a set of algorithms to automatically evaluate motility measurements. I reported a qualitative and

quantitative experimental assessment based on a set of data we acquired with the help of volunteers which spent some days or hours in the apartment. The corresponding acquisition thus represents a suitable test-bed for the analysis of daily-life activities.

6.2 Final discussion

This work opens the way for possible future developments and responds to several open challenges in the domain of smart systems:

- *Usability and generality.* The conceptual model can be seen as a proof-of-concept of a wider variety of environments and situations. It does not rely on any specificity of the installation, and could be easily adapted to private homes or protected residences. The hardware set up is low cost, easily configurable, and it does not need to obey specific constraints. The only issue to be considered is the problem of occlusions, therefore it is advisable to avoid excess furniture.
- *Accessibility.* As an assistive tool, the proposed model is not used directly by the patient. The end-user of the technology is the physician, and the proposed model is highly accessible to them, as it produces reports which have been designed in close collaboration with doctors and are based on the type of questionnaires they normally use to assess the patient's health status. Instead, for the patient, there is no accessibility issue to consider as he/she should be virtually unaware of the monitoring installation. In the proposed model patients have to interact only with health devices which have proved to be unsuitable. In the future it would be better to replace them with wearable sensors
- *Robustness.* The whole model of protected discharge is undergoing a live test, that started nearly three years ago. The various components including the vision-based one I have discussed in this thesis, have been continuously evaluated and quantitative tests are carried out each time a new computational model is inserted or updated. Quantitative tests, requiring a manual annotation of actions performed by the subjects, are only performed with the help of volunteers. Current tests did not highlight any specific issue, while instead the system appears to be robust to illumination changes and to scene variations.

For more specific tasks involving ADL, different sensors and algorithms would be needed, as we will briefly discuss in the next section.

- *Usefulness.* Considering the steady growth of elderly population, the proposed model has a potential impact on the society which goes beyond the specific problem we have considered. The same model could be an inspiration for home-monitoring systems, with a clear impact on an aging society where individual autonomy is fundamental.

More specifically, we are ready to discuss some of the main open issues for the model, highlighted in Section 2.7 and taking into account the outcomes of my project, I may now provide answers to some relevant open issues:

- *What are the minimal requirements?* As it clearly emerged from my experimental analysis, for an effective continuous assessment of patients motility the observation needs to be carried out for some time, to be able to capture meaningful information and associate reliable estimates. As I pointed out in Section 5.5, I observed volunteers for at least two hours. This time may not be sufficient to implement valid statistical tool to understand patients behavior and habits. This observational time is also not enough to obtain information on volunteer health status, clinical parameters indeed have to be acquired twice a day for some days in order to study the evolution of them. To ensure that the short observation time is still informative enough, users should be encouraged to carry out activities. For instance, leaving a snack by the kitchen or fresh water in the fridge could encourage them to perform instrumental activities and walk across the room. Additionally, it would be very useful to create stimuli to obtain more reliable quantitative measurements (e.g., ring the door bell to guarantee the patient is going to walk towards a given, predefined direction: this would be useful for a reliable estimate of velocity).
- *How to guarantee a good spatial-temporal coverage of the continuous assessment?* The challenge is to analyze day and night indoor environments of variable size and complexity. As pointed out in Chapter 3 the facility has redundant sensors distributed in the environment. Redundant measurements, heterogeneous sensors, and multiple dimensions are an important aspect of my approach and should be enhanced and fully exploited; different sensors have different precision in space and time (e.g., cameras provide limited information during

the night and no information in privacy protected areas such as toilettes), and some areas are more informative than others and thus would require an extra care, and possibly the coverage of multiple sources.

- *How to merge and complement automatic continuous assessment and sporadic domain-expert analysis?* In my analysis, the assessment inferred by the continuous automatic analysis is currently provided as a separate report. As an insight for future research, it would be worth investigating the benefit in integrating the output of manual tests within the automatic analysis procedure. This could be applied to both manual tests on frailty and cognitive status as well as other clinical observations.
- *How to incorporate the patient's specificities?* A common practice in continuous data analysis is to set up a training phase during which the system is calibrated and tuned to meet the specificity of a given environment or situation. This would imply adjusting parameters and fine tuning the system to better reflect the user's habits. This approach is appropriate in the case of a long-term analysis and it is instead less effective in short-term continuous evaluations. To mitigate this issue, one could exploit the doctor's opinion after check in, to derive meaningful information on the patient's abilities to be used as a guideline for the following automatic assessment.
- *Can this model participate in a more general healthcare data collection?* Healthcare data come from very heterogeneous sources. They may be structured, unstructured, and semi-structured data types, including laboratory results, medications prescriptions, clinical observations such as physicians diagnosis, recommendations, discharge summaries or operative reports. All these quantitative and qualitative data describe the patient from different points of view, but they are often difficult to integrate. The availability of state-of-the-art data analysis tools will provide, in the years to come, an up-to-date profile of the overall health status of the patient, to be shared among specialists, general practitioners, and families.
- *How to satisfy user needs, acceptability and satisfaction?* Satisfying the needs of the user is a major challenge. One of the problem in this task is the fact that elderly patients refuse to use technological devices because they do not think to really need them or, in other case, because they do not understand how to

use them. Elderly people generally do not feel comfortable with technology so they simply avoid it. They also prefer direct relation with doctor and nurses, because it is a social occasion. Last but not least they refuse to wear medical or tele-health devices because they reduced their level of self-esteem. In my project I had to deal with the relationship between elderly and technology, and, as I pointed out in Section 5.2 most of the elderly volunteers had no confidence with smart phones and had difficulties in selecting icons and record measures. The recommendation is to consider users' needs and choose the suitable technologies, which will help elderly to express their needs, improve their quality of care and comfort.

- *How to guarantee reliability and efficiency of sensory systems and data processing software?* As the mobility, activity and vital signs of a monitored subject will be processed by algorithms to detect and signal dangerous situations, the accuracy of the input data is paramount. In terms of mobility and activity, the goal is to locate a person within their home and model their habitual movements. An alarm is triggered when the person deviates from this routine by more than some predefined threshold. Several methods are used for deciding when an alarm should be triggered: neural networks, Markov chains, machine learning and predictive algorithms, decision trees, statistical models, probabilistic models, classification, etc. In all these cases, it is necessary to measure a lifestyle: the person being monitored must have consistent habits in the first place for the system to work. To sum up, all these home care systems must provide reliable positioning and measurement of vital signs; have a reliable algorithm for evaluating the patient's "lifestyle"; trigger an alarm in case of danger; correctly interpret the vital signs through automated software or a competent medical professional, so that deficient function can be recognized; organize emergency response rapidly and effectively in case of need.

On this respect, the outcome of an automatic assessment of frailty could be a meaningful complementary part of this general picture, providing additional information and automatic measurements, for a better tailored treatment and follow-up.

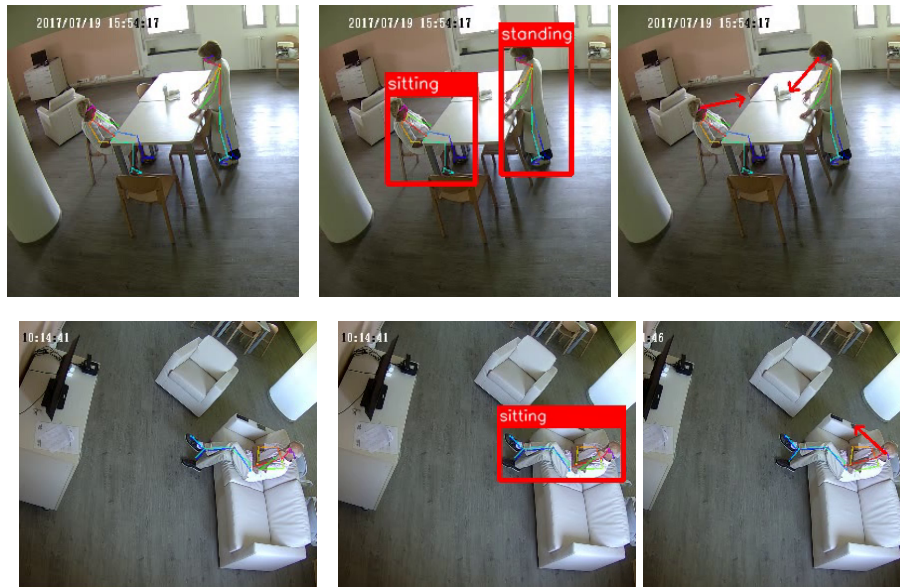


Figure 6.1 Preliminary results in video analysis. Left: 2D pose estimation; center: pose classification; right: gaze direction estimation.

6.3 Future works

The MoDiPro project inspired and motivated different lines of research, which will be carried out in the near future. In this final analysis of future development I focus on computational vision methods for their closer relationship to my work. The motility analysis I presented is based on skeletal information obtained by RGB-D sensors, while for more complex ADL assessment, video-based methods would be necessary. An interesting possibility would be to exploit recently proposed very effective methods to estimate 2D poses, such as the OpenPose (Cao et al., 2016). From these estimates we could derive motility measurements, complementary to the ones we are computing with RGB-D (Figure 6.1, center), as well as more precise estimates, which could be useful to infer human activities (such as gaze direction estimation shown in Figure 6.1 right, that could help us analyzing socialization cues, or understanding how the patient interacts with the environment). Preliminary results are encouraging us to continue our research on this path.

6.4 Publications

Conference papers

- Paper accepted at Foritaal, 9 Th Forum Italiano Ambient Assisted Living, 2/4 July 2018, Lecce, Italy Carlotta Patrone, Chiara Martini, Alberto Cella, Annalisa Barla, Fulvio Mastrogovanni, Francesca Odone, Nicolo' Casiddu, Silvia Pericu, Claudia Porirone, Raffaella Boi, Matteo Puntoni, Alessandro Verri, Alberto Pilotto. Development of a smart technology based post hospitalization facility for older people.
- Paper accepted at VISAPP, 13Th International Conference on Computer Vision Theory and Application, Funchal, Madeira, Portugal 27/29 January 2018 Chiara Martini, Annalisa Barla, Manuela Chessa, Fabio Solari, Nicoletta Noceti, Francesca Odone, Alessandro Verri. A visual computing approach for estimating the Motility Index in the frail elder.
- Paper published on the proceedings of IEEE EMBC 2017, 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Jeju Island, Korea. Samuele Fiorini, Chiara Martini, Davide Malpassi, Renzo Cordera, Davide Maggi, Alessandro Verri, and Annalisa Barla. Data-driven strategies for robust forecast of continuous glucose monitoring time-series.

Book Chapter

- M.Chessa, N.Noceti,C.Martini, F. Solari, and F. Odone, "Design of assistive tools for the market," in Assistive Computer Vision, M. Leo and G. Farinella, Eds. Elsevier, 2017.
- C. Martini, F. Odone, N.Noceti, M. Chessa, A. Barla, A. Cella, A. Pilotto, G. A. Rollandi and A. Verri. "Visual computing methods for assessing the well-being of older people", (SUBMITTED) Springer

Journal paper

- C. Martini, N. Noceti, A. Barla, F. Odone. "Data-driven continuous assessment of frailty in older people", Frontiers in Digital Humanities.

6.5 Oral presentations and Posters

Oral presentation

- Foritaal, 9th Forum Italiano Ambient Assisted Living, 2/4 July 2018, Lecce, Italy
- BMVA Symposium on Computer Vision for smart environments and assisted living, 13 June 2018, London, UK
- VISAPP, 13Th International Conference on Computer Vision Theory and Application, Funchal, Madeira, Portugal 27/29 January 2018

Poster presentation

- BMVA Symposium on Computer Vision for smart environments and assisted living, 13 June 2018, London, UK
- 31st Congresso Nazionale SIGOT, Società Italiana di Geriatria Ospedale e Territorio. 8/9 June 2017, Palazzo Ducale, Genova, Italy

References

- Adair, B., Miller, K., Ozanne, E., Hansen, R., Pearce, A. J., Santamaria, N., Viegas, L., Long, M., and Said, C. M. (2013). Smart-home technologies to assist older people to live well at home. *Journal of Aging Science*.
- Adami, A. M., Pavel, M., Hayes, T. L., and Singer, C. M. (2010). Detection of movement in bed using unobtrusive load cell sensors. *IEEE Trans. Information Technology in Biomedicine*, 14(2):481–490.
- Aminuddin, R., Sharkey, A., and Levita, L. (2016). Interaction with the paro robot may reduce psychophysiological stress responses. In *Human-Robot Interaction (HRI), 2016 11th ACM/IEEE International Conference on*, pages 593–594. IEEE.
- Angleman, S. B., Santoni, G., Pilotto, A., Fratiglioni, L., Welmer, A.-K., Investigators, M. P., et al. (2015). Multidimensional prognostic index in association with future mortality and number of hospital days in a population-based sample of older adults: results of the EU funded MPI_AGE project. *PloS one*, 10(7):e0133789.
- Azzopardi, R. V., Vermeiren, S., Gorus, E., Habbig, A.-K., Petrovic, M., Van Den Noortgate, N., De Vriendt, P., Bautmans, I., Beyer, I., Verté, D., et al. (2016). Linking frailty instruments to the international classification of functioning, disability, and health: a systematic review. *Journal of the American Medical Directors Association*, 17(11):1066–e1.
- Banerjee, T., Rantz, M., Li, M., Popescu, M., Stone, E., Skubic, M., and Scott, S. (2012). Monitoring hospital rooms for safety using depth images. *AI for Gerontechnology, Arlington, Virginia, US*.
- Bari, M., Virgillo, A., Matteuzzi, D., Inzitari, M., Mazzaglia, G., Pozzi, C., Geppetti, P., Masotti, G., Marchionni, N., and Pini, R. (2006). Predictive validity of measures of comorbidity in older community dwellers: the insufficienza cardiaca negli anziani residenti a dicomano study. *Journal of the American Geriatrics Society*, 54(2):210–216.
- Barlow, J. and Venables, T. (2004). Will technological innovation create the true lifetime home? *Housing Studies*, 19(5):795–810.
- Bathrinarayanan, V., Fosty, B., Konig, A., Romdhane, R., Thonnat, M., Bremond, F., et al. (2013). Evaluation of a monitoring system for event recognition of older people. In *Advanced Video and Signal Based Surveillance (AVSS), 2013 10th IEEE International Conference on*, pages 165–170.

- Bliss, M., McLaren, R., and Exton-Smith, A. (1966). Mattresses for preventing pressure sores in geriatric patients. *Monthly Bulletin of the Ministry of Health and the Public Health Laboratory Service*, 25:238–268.
- Bouchard, B., Giroux, S., and Bouzouane, A. (2007). A keyhole plan recognition model for alzheimer's patients: First results. *Applied Artificial Intelligence*, 21(7):623–658.
- Brodaty, H., Pond, D., Kemp, N. M., Luscombe, G., Harding, L., Berman, K., and Huppert, F. A. (2002). The gpcog: a new screening test for dementia designed for general practice. *Journal of the American Geriatrics Society*, 50(3):530–534.
- Brown, A. S., Brummel-Smith, K., Burgess, L., D'Agostino, R. B., Goldschmidt, J. W., Halter, J. B., Hazzard, W. R., Jahnigen, D. W., Phelps, C., Raskind, M., et al. (1988). National institutes of health consensus development conference statement: Geriatric assessment methods for clinical decision-making. *Journal of the American Geriatrics Society*, 36(4):342–347.
- Canessa, A., Chessa, M., Gibaldi, A., Sabatini, S. P., and Solari, F. (2014). Calibrated depth and color cameras for accurate 3d interaction in a stereoscopic augmented reality environment. *Journal of Visual Communication and Image Representation*, 25(1):227–237.
- Cao, Y., Tao, L., and Xu, G. (2009). An event-driven context model in elderly health monitoring. In *Ubiquitous, Autonomic and Trusted Computing, 2009. UIC-ATC'09. Symposia and Workshops on*, pages 120–124. IEEE.
- Cao, Z., Simon, T., Wei, S.-E., and Sheikh, Y. (2016). Realtime multi-person 2d pose estimation using part affinity fields. *arXiv preprint arXiv:1611.08050*.
- Chan, M., Campo, E., and Estève, D. (2005). Assessment of activity of elderly people using a home monitoring system. *International Journal of Rehabilitation Research*, 28(1):69–76.
- Chan, M., Campo, E., Estève, D., and Fourniols, J.-Y. (2009). Smart homes—current features and future perspectives. *Maturitas*, 64(2):90–97.
- Chan, M., Estève, D., Escriba, C., and Campo, E. (2008). A review of smart homes—present state and future challenges. *Computer methods and programs in biomedicine*, 91(1):55–81.
- Chessa, M., Noceti, N., Martini, C., Solari, F., and Odone, F. (2017). Design of assistive tools for the market. In Leo, M. and Farinella, G., editors, *Assistive Computer Vision*. Elsevier.
- Clark, R. A., Pua, Y.-H., Fortin, K., Ritchie, C., Webster, K. E., Denehy, L., and Bryant, A. L. (2012). Validity of the microsoft kinect for assessment of postural control. *Gait & posture*, 36(3):372–377.

- Clegg, A., Bates, C., Young, J., Ryan, R., Nichols, L., Ann Teale, E., Mohammed, M. A., Parry, J., and Marshall, T. (2016). Development and validation of an electronic frailty index using routine primary care electronic health record data. *Age and ageing*, 45(3):353–360.
- Courtney, K. L. (2008). *Privacy and senior willingness to adopt smart home information technology in residential care facilities*. Schattauer.
- Courtney, K. L., Demeris, G., Rantz, M., and Skubic, M. (2008). *Needing smart home technologies: the perspectives of older adults in continuing care retirement communities*. Radcliffe Medical Press.
- De Vries, N., Staal, J., Van Ravensberg, C., Hobbelen, J., Rikkert, M. O., and Nijhuis-Van der Sanden, M. (2011). Outcome instruments to measure frailty: a systematic review. *Ageing research reviews*, 10(1):104–114.
- Dent, E., Kowal, P., and Hoogendijk, E. O. (2016). Frailty measurement in research and clinical practice: a review. *European journal of internal medicine*, 31:3–10.
- Ding, D., Cooper, R. A., Pasquina, P. F., and Fici-Pasquina, L. (2011). Sensor technology for smart homes. *Maturitas*, 69(2):131–136.
- Folstein, M. F., Folstein, S. E., and McHugh, P. R. (1975). “mini-mental state”: a practical method for grading the cognitive state of patients for the clinician. *Journal of psychiatric research*, 12(3):189–198.
- Franceschi, M., Scarcelli, C., Niro, V., Seripa, D., Pazienza, A. M., Pepe, G., Colusso, A. M., Pacilli, L., and Pilotto, A. (2008). Prevalence, clinical features and avoidability of adverse drug reactions as cause of admission to a geriatric unit. *Drug safety*, 31(6):545–556.
- Fried, L. P., Ferrucci, L., Darer, J., Williamson, J. D., and Anderson, G. (2004). Untangling the concepts of disability, frailty, and comorbidity: implications for improved targeting and care. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 59(3):M255–M263.
- Fujita, M. (2001). Aibo: Toward the era of digital creatures. *The International Journal of Robotics Research*, 20(10):781–794.
- Gao, L., Bourke, A. K., and Nelson, J. (2012). Activity recognition using dynamic multiple sensor fusion in body sensor networks. In *Engineering in Medicine and Biology Society (EMBC), 2012 annual international conference of the IEEE*, pages 1077–1080.
- Gazzola, A. (2011). *Uno sguardo diverso: la percezione sociale dello spazio naturale e costruito*. FrancoAngeli.
- Gianaria, E., Grangetto, M., Roppolo, M., Mulasso, A., and Rabaglietti, E. (2016). Kinect-based gait analysis for automatic frailty syndrome assessment. In *2016 IEEE International Conference on Image Processing (ICIP)*, pages 1314–1318. IEEE.

- Giannakouris, K. (2008). Ageing characterises the demographic perspectives of the european societies. *Statistics in focus*, 72:2008.
- Gloth III, F. M., Scheve, A. A., Shah, S., Ashton, R., and McKinney, R. (1999). The frail elderly functional assessment questionnaire: its responsiveness and validity in alternative settings. *Archives of physical medicine and rehabilitation*, 80(12):1572–1576.
- Gobbens, R. J., van Assen, M. A., Luijckx, K. G., Wijnen-Sponselee, M. T., and Schols, J. M. (2010). The tilburg frailty indicator: psychometric properties. *Journal of the American Medical Directors Association*, 11(5):344–355.
- Greene, B. R., Doheny, E. P., O'halloran, A., and Anne Kenny, R. (2013). Frailty status can be accurately assessed using inertial sensors and the tug test. *Age and ageing*, 43(3):406–411.
- Guigoz, Y. and Vellas, B. (1999). The mini nutritional assessment (mna) for grading the nutritional state of elderly patients: presentation of the mna, history and validation. In *Mini Nutritional Assessment (MNA): Research and Practice in the Elderly*, volume 1, pages 3–12. Karger Publishers.
- Hartley, R. and Zisserman, A. (2003). *Multiple view geometry in computer vision*. Cambridge university press.
- Helal, S., Mann, W., El-Zabadani, H., King, J., Kaddoura, Y., and Jansen, E. (2005). The gator tech smart house: A programmable pervasive space. *Computer*, 38(3):50–60.
- Hoyl, M. T., Alessi, C. A., Harker, J. O., Josephson, K. R., Pietruszka, F. M., Koelfgen, M., Mervis, J. R., Fitten, L. J., and Rubenstein, L. Z. (1999). Development and testing of a five-item version of the geriatric depression scale. *Journal of the American Geriatrics Society*, 47(7):873–878.
- Jolliffe, I. (2005). Principal component analysis: Wiley online library. *Google Scholar*.
- Joumier, V., Romdhane, R., Bremond, F., Thonnat, M., Mulin, E., Robert, P., Derreumaux, A., Piano, J., and Lee, J. (2011). Video activity recognition framework for assessing motor behavioural disorders in Alzheimer disease patients. In *International Workshop on Behaviour Analysis and Video Understanding (ICVS 2011)*, page 9.
- Kanade, T. (2012). Quality of life technology [scanning the issue]. *Proceedings of the IEEE*, 100(8):2394–2396.
- Kartakis, S., Sakkalis, V., Tournakis, P., Zacharioudakis, G., and Stephanidis, C. (2012). Enhancing health care delivery through ambient intelligence applications. *Sensors*, 12(9):11435–11450.
- Katz, S., Downs, T. D., Cash, H. R., and Grotz, R. C. (1970). Progress in development of the index of adl. *The gerontologist*, 10(1_Part_1):20–30.

- Kientz, J. A., Patel, S. N., Jones, B., Price, E., Mynatt, E. D., and Abowd, G. D. (2008). The georgia tech aware home. In *CHI'08 extended abstracts on Human factors in computing systems*, pages 3675–3680. ACM.
- Kirkwood, T. B. (2008). A systematic look at an old problem. *Nature*, 451(7179):644.
- Lafont, C., Gérard, S., Voisin, T., Pahor, M., Vellas, B., et al. (2011). Reducing “iatrogenic disability” in the hospitalized frail elderly. *The journal of nutrition, health & aging*, 15(8):645–660.
- Lau, D. T., Kasper, J. D., Potter, D., Lyles, A., and Bennett, R. G. (2005). Hospitalization and death associated with potentially inappropriate medication prescriptions among elderly nursing home residents. *Archives of internal medicine*, 165(1):68–74.
- Lawton MP, B. E. (1969). Assessment of older people: self-maintaining and instrumental activities of daily living. *The gerontologist*, 9:179–86.
- LeBellego, G., Noury, N., Virone, G., Mousseau, M., and Demongeot, J. (2006). A model for the measurement of patient activity in a hospital suite. *IEEE Transactions on information technology in biomedicine*, 10(1):92–99.
- Lenzi, J., Mongardi, M., Rucci, P., Di Ruscio, E., Vizioli, M., Randazzo, C., Toschi, E., Carradori, T., and Fantini, M. P. (2014). Sociodemographic, clinical and organisational factors associated with delayed hospital discharges: a cross-sectional study. *BMC health services research*, 14(1):128.
- Lera, F. J., Rodríguez, V., Rodríguez, C., and Matellán, V. (2014). Augmented reality in robotic assistance for the elderly. In *International Technology Robotics Applications*, pages 3–11. Springer.
- Linn, B. S., LINN, M. W., and Gurel, L. (1968). Cumulative illness rating scale. *Journal of the American Geriatrics Society*, 16(5):622–626.
- Liu, R. and Liu, M. (2010). Recognizing human activities based on multi-sensors fusion. In *Bioinformatics and Biomedical Engineering (iCBBE), 2010 4th International Conference on*, pages 1–4. IEEE.
- Maaten, L. v. d. and Hinton, G. (2008). Visualizing data using t-sne. *Journal of machine learning research*, 9(Nov):2579–2605.
- Martini, C., Barla, A., Odone, F. O., Verri, A., Rollandi, G. A., and Pilotto, A. (2018a). Data-driven continuous assessment of frailty in older people. *Frontiers in Digital Humanities*, 5:6.
- Martini, C., Noceti, N., Chessa, M., Barla, A., Cella, A., Rollandi, Gian Andrea Pilotto, A. V. A., and Odone, F. (2018b). Visual computing approach for estimating the motility index in the frail elder. *13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*.

- Martini, C., Odone, F., Noceti, N., Chessa, M., Barla, A., Cella, A., Pilotto, A., Rollandi, G. A., and Verri, A. (2018c). Visual computing methods for assessing the well-being of older people. (UNDER REVIEW) Springer.
- Maslow, A. H. (1943). A theory of human motivation. *Psychological review*, 50(4):370.
- Mulasso, A., Roppolo, M., Gobbens, R. J., and Rabaglietti, E. (2016). The italian version of the tilburg frailty indicator: analysis of psychometric properties. *Research on aging*, 38(8):842–863.
- Nick, M. and Becker, M. (2007). A hybrid approach to intelligent living assistance. In *Hybrid Intelligent Systems, 2007. HIS 2007. 7th International Conference on*, pages 283–289. IEEE.
- Nishida, Y., Hori, T., Suehiro, T., and Hirai, S. (2000). Sensorized environment for self-communication based on observation of daily human behavior. In *Intelligent Robots and Systems, 2000.(IROS 2000). Proceedings. 2000 IEEE/RSJ International Conference on*, volume 2, pages 1364–1372. IEEE.
- Pantelopoulos, A. and Bourbakis, N. G. (2010). A survey on wearable sensor-based systems for health monitoring and prognosis. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 40(1):1–12.
- Patel, S., Park, H., Bonato, P., Chan, L., and Rodgers, M. (2012). A review of wearable sensors and systems with application in rehabilitation. *Journal of neuroengineering and rehabilitation*, 9(1):21.
- Patrone, C., Martini, C., Cella, A., Barla, A., Fulvio, M., Odone, F., Casiddu, N., Pericu, S., Porirone, C., Boi, R., Puntoni, M., Verri, A., and Pilotto, A. (2018). Development of a smart technology based post hospitalization facility for older people. *9Th Forum Italiano Ambient Assisted Living*.
- Perry, M., Dowdall, A., Lines, L., and Hone, K. (2004). Multimodal and ubiquitous computing systems: supporting independent-living older users. *IEEE Transactions on information technology in biomedicine*, 8(3):258–270.
- Pfeiffer, E. (1975). A short portable mental status questionnaire for the assessment of organic brain deficit in elderly patients. *Journal of the American Geriatrics Society*, 23(10):433–441.
- Pierce, D. (2012). *The accessible home: designing for all ages and abilities*. Taunton Press.
- Pigini, L., Bovi, G., Panzarino, C., Gower, V., Ferratini, M., Andreoni, G., Sassi, R., Rivolta, M. W., and Ferrarin, M. (2017). Pilot test of a new personal health system integrating environmental and wearable sensors for telemonitoring and care of elderly people at home (smarta project). *Gerontology*, 63(3):281–286.
- Pilotto, A., Ferrucci, L., Franceschi, M., D’Ambrosio, L. P., Scarcelli, C., Cascavilla, L., Paris, F., Placentino, G., Seripa, D., Dallapiccola, B., et al. (2008). Development and validation of a multidimensional prognostic index for one-year mortality from comprehensive geriatric assessment in hospitalized older patients. *Rejuvenation research*, 11(1):151–161.

- Pilotto, A., Ferrucci, L., Scarcelli, C., Niro, V., Di Mario, F., Seripa, D., Andriulli, A., Leandro, G., and Franceschi, M. (2007). Usefulness of the comprehensive geriatric assessment in older patients with upper gastrointestinal bleeding: a two-year follow-up study. *Digestive Diseases*, 25(2):124–128.
- Pilotto, A., Rengo, F., Marchionni, N., Sancarlo, D., Fontana, A., Panza, F., Ferrucci, L., study group, F.-S., et al. (2012). Comparing the prognostic accuracy for all-cause mortality of frailty instruments: a multicentre 1-year follow-up in hospitalized older patients. *PloS one*, 7(1):e29090.
- Pollack, M. E., Brown, L., Colbry, D., Orosz, C., Peintner, B., Ramakrishnan, S., Engberg, S., Matthews, J. T., Dunbar-Jacob, J., McCarthy, C. E., et al. (2002). Pearl: A mobile robotic assistant for the elderly. In *AAAI workshop on automation as eldercare*, volume 2002, pages 85–91.
- Rantz, M. J., Skubic, M., Koopman, R. J., Phillips, L., Alexander, G. L., Miller, S. J., and Guevara, R. D. (2011). Using sensor networks to detect urinary tract infections in older adults. In *e-Health Networking Applications and Services (Healthcom), 2011 13th IEEE International Conference on*, pages 142–149. IEEE.
- Rashidi, P. and Cook, D. J. (2009). Keeping the resident in the loop: Adapting the smart home to the user. *IEEE Transactions on systems, man, and cybernetics-part A: systems and humans*, 39(5):949–959.
- Robinson, H., MacDonald, B., and Broadbent, E. (2014). The role of healthcare robots for older people at home: A review. *International Journal of Social Robotics*, 6(4):575–591.
- Rockwood, K., Theou, O., and Mitnitski, A. (2015). What are frailty instruments for? *Age and ageing*, 44(4):545–547.
- Roppolo, M., Mulasso, A., Gobbens, R. J., Mosso, C. O., and Rabaglietti, E. (2015). A comparison between uni- and multidimensional frailty measures: prevalence, functional status, and relationships with disability. *Clinical interventions in aging*, 10:1669.
- Santagostino, P. (2006). Il colore in casa. *Urra, Milano*, 16.
- Scanail, C. N., Carew, S., Barralon, P., Noury, N., Lyons, D., and Lyons, G. M. (2006). A review of approaches to mobility telemonitoring of the elderly in their living environment. *Annals of biomedical engineering*, 34(4):547–563.
- Schulz, R., Beach, S. R., Matthews, J. T., Courtney, K. L., and Dabbs, A. J. D. V. (2012). Designing and evaluating quality of life technologies: An interdisciplinary approach. *Proceedings of the IEEE*, 100(8):2397–2409.
- Schuermans, H., Steverink, N., Lindenberg, S., Frieswijk, N., and Slaets, J. P. (2004). Old or frail: what tells us more? *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 59(9):M962–M965.

- Spooner, D. and Pachan, N. (2006). Ecological validity in neuropsychological assessment: A case for greater consideration in research with neurologically intact populations. *Archives of Clinical Neuropsychology*, 21(4):327–337.
- Strawbridge, W. J., Shema, S. J., Balfour, J. L., Higby, H. R., and Kaplan, G. A. (1998). Antecedents of frailty over three decades in an older cohort. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 53(1):S9–S16.
- Tamura, T., Kawarada, A., Nambu, M., Tsukada, A., Sasaki, K., and Yamakoshi, K.-I. (2007). E-healthcare at an experimental welfare techno house in japan. *The open medical informatics journal*, 1:1.
- Uddin, M., Khaksar, W., and Torresen, J. (2018). Ambient sensors for elderly care and independent living: a survey. *Sensors*, 18(7):2027.
- Vacher, M., Istrate, D., Portet, F., Joubert, T., Chevalier, T., Smidtas, S., Meillon, B., Lecouteux, B., Sehili, M., Chahuara, P., et al. (2011). The sweet-home project: Audio technology in smart homes to improve well-being and reliance. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 5291–5294.
- Van Berlo, A. (1998). A smart model house as research and demonstration tool for telematics development. In *Proc. 3rd TIDE Congres: Technology for Inclusive Design and Equality Improving the Quality of Life for the European Citizen*, volume 23, page 25.
- van Breemen, A., Yan, X., and Meerbeek, B. (2005). icat: an animated user-interface robot with personality. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*, pages 143–144. ACM.
- Visutsak, P. and Daoudi, M. (2017). The smart home for the elderly: Perceptions, technologies and psychological accessibilities: The requirements analysis for the elderly in thailand. In *Information, Communication and Automation Technologies (ICAT), 2017 XXVI International Conference on*, pages 1–6. IEEE.
- Volpato, S., Bazzano, S., Fontana, A., Ferrucci, L., and Pilotto, A. (2014). Multi-dimensional prognostic index predicts mortality and length of stay during hospitalization in the older patients: a multicenter prospective study. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences*, 70(3):325–331.
- Volpato, S., Daragjati, J., Simonato, M., Fontana, A., Ferrucci, L., and Pilotto, A. (2016). Change in the multidimensional prognostic index score during hospitalization in older patients. *Rejuvenation research*, 19(3):244–251.
- Volpato, S., Onder, G., Cavalieri, M., Guerra, G., Sioulis, F., Maraldi, C., Zuliani, G., Fellin, R., of Pharmacoepidemiology in the Elderly Study (GIFA, I. G., et al. (2007). Characteristics of nondisabled older patients developing new disability associated with medical illnesses and hospitalization. *Journal of general internal medicine*, 22(5):668–674.

- Wada, K. and Shibata, T. (2007). Living with seal robots—its sociopsychological and physiological influences on the elderly at a care house. *IEEE Transactions on Robotics*, 23(5):972–980.
- Warnier, R., Van Rossum, E., Van Velthuijsen, E., Mulder, W., Schols, J., and Kempen, G. (2016). Validity, reliability and feasibility of tools to identify frail older patients in inpatient hospital care: a systematic review. *The journal of nutrition, health & aging*, 20(2):218–230.
- Wichert, R. and Eberhardt, B. (2012). *Ambient assisted living*. Springer.
- Youngblood, G. M., Cook, D. J., and Holder, L. B. (2005). Managing adaptive versatile environments. *Pervasive and Mobile Computing*, 1(4):373–403.
- Zouba, N., Boulay, B., Bremond, F., and Thonnat, M. (2008). Monitoring activities of daily living (ADLs) of elderly based on 3D key human postures. In *Cognitive Vision*, pages 37–50. Springer.
- Zouba, N., Bremond, F., and Thonnat, M. (2010). An activity monitoring system for real elderly at home: Validation study. In *Advanced Video and Signal Based Surveillance (AVSS), 2010 Seventh IEEE International Conference on*, pages 278–285. IEEE.

Appendix A

MPI

ACTIVITIES OF DAILY LIVING (ADL) *

A) BATHING (either sponge bath, tub bath, or shower)	
- Receives no assistance (gets in and out of tub by self if tub is usual means of bathing)	1
- Receives assistance in bathing only one part of the body (such as back or a leg)	1
- Receives assistance in bathing more than one part of the body (or not bathed)	0
B) DRESSING (gets clothes from closets and drawers – including underclothes, outer garments, and using fasteners including braces, if worn)	
- Gets clothes and gets completely dressed without assistance	1
- Gets clothes and gets dressed without assistance except for assistance in tying shoes	1
- Receives assistance in getting clothes or in getting dressed, or stays partly or completely undressed	0
C) TOILETING (going to the "toilet room" for bowel and urine elimination, cleaning self after elimination, and arranging clothes)	
- Goes to "toilet room," cleans self, and arranges clothes without assistance (may use object for support such as cane, walker, or wheelchair and may manage night bedpan or commode, emptying same in morning)	1
- Receives assistance in going to "toilet room" or in cleaning self or in arranging clothes after elimination or in use of night bedpan or commode	0
- Doesn't go to room termed "toilet" for the elimination process	0
D) TRANSFER	
- Moves in and out of bed as well as in and out of chair without assistance (may be using object for support such as cane or walker)	1
- Moves in and out of bed or chair with assistance	0
- Doesn't get out of bed	0
E) CONTINENCE	
- Controls urination and bowel movement completely by self	1
- Has occasional "accidents"	0
- Supervision helps keep urine or bowel control, catheter is used, or is incontinent	0
F) FEEDING	
- Feeds self without assistance	1
- Feeds self except for getting assistance in cutting meat or buttering bread	1
- Receives assistance in feeding or is fed partly or completely by using tubes or intravenous fluids	0

TOTAL _____

* Katz S, Ford AB, Moskowitz RW et al. *Studies of illness in the aged. The index of ADL: A standardized measure of biological and psychological function.* JAMA 1963; 185: 914-19.

INSTRUMENTAL ACTIVITIES OF DAILY LIVING SCALE (IADL)*

A) ABILITY TO USE TELEPHONE	
- Operates telephone on own initiative: looks up and dials numbers, etc.	1
- Dials a few well-known numbers	1
- Answers telephone but does not dial	1
- Does not use telephone at all	0
B) SHOPPING	
- Takes care of all shopping needs independently	1
- Shops independently for small purchases	0
- Needs to be accompanied on any shopping trip	0
- Completely unable to shop	0
C) FOOD PREPARATION	
- Plans, prepares and serves adequate meals independently	1
- Prepares adequate meals if supplied with ingredients	0
- Heats, serves and prepares meals or prepares meals but does not maintain adequate diet	0
- Needs to have meals prepared and served	0
D) HOUSEKEEPING	
- Maintains house alone or with occasional assistance (e.g. "heavy work domestic help")	1
- Performs light daily tasks such as dishwashing, bed making, etc.	1
- Performs light daily tasks but cannot maintain acceptable level of cleanliness	1
- Needs help with all home maintenance tasks	0
- Does not participate in any housekeeping tasks	0
E) LAUNDRY	
- Does personal laundry completely	1
- Launders small items; rinses stockings, etc.	1
- All laundry must be done by others	0
F) MODE OF TRANSPORTATION	
- Travels independently on public transportation or drives own car	1
- Arranges own travel via taxi, but does not otherwise use public transportation	1
- Travels on public transportation when accompanied by another	1
- Travel limited to taxi or automobile with assistance of another	0
- Does not travel at all	0
G) RESPONSIBILITY FOR OWN MEDICATIONS	
- Is responsible for taking medication in correct dosages at correct time	1
- Takes responsibility if medication is prepared in advance in separate dosage	0
- Is not capable of dispensing own medication	0
H) ABILITY TO HANDLE FINANCES	
- Manages financial matters independently (budgets, writes checks, pays rent, bills goes to bank), collects and keeps track of income	1
- Manages day-to-day purchases, but needs help with banking, major purchases, etc.	1
- Incapable if handling money	0

TOTAL _____

* Lawton MP, Brody EM. Assessment of older people: self-maintaining and instrumental activities of daily living. *Gerontologist* 1969;9:179-86.

**SHORT PORTABLE MENTAL STATUS
QUESTIONNAIRE (SPMSQ) ***
(Record the errors)

What is the date today? (Correct only when the month, date, and year are all correct)	1
What day of the week is it?	1
What is the name of this place? (Correct if any of the description of the location is given)	1
What is your street address?	1
How old are you?	1
When were you born?	1
Who is the president (or the Pope) now? (Requires only the correct last name)	1
Who was president (or the Pope) just before him?	1
What was your mother's maiden name?	1
Subtract 3 from 20 and keep subtracting 3 from each new number at least for 3 times (The entire series must be performed correctly to be scored as correct)	1

TOTAL _____

** Pfeiffer E. A short portable mental status questionnaire for the assessment of organic brain deficit in elderly patients. J Am Geriatr Soc. 1975; 23:433-441.*

EXTON-SMITH SCALE (ESS) *
(evaluation of pressure sores risk)

General Condition		Incontinence	
Bad	1	Doubly incontinent	1
Poor	2	Usually of urine	2
Fair	3	Occasional	3
Good	4	Not	4
Mental State		Mobility in Bed	
Stuporosos	1	Immobile	1
Confused	2	Very limited	2
Apathetic	3	Slightly limited	3
Alert	4	Full	4
Activity		TOTAL _____	
In bed all day	1	Score 16-20: minimum risk Score 10-15: medium risk Score 5-9: high risk	
Chairfast	2		
Walks with help	3		
Ambulant	4		

** Bliss MR., McLaren R., Exton-Smith AN. Mattresses for preventing pressure sores in geriatric patients. Mon Bull Minist Health Public Health Lab Serv 1966*

MINI NUTRITIONAL ASSESSMENT (MNA) *

A) Anthropometric Assessment

1) Body Mass Index (BMI) Weight: _____ kg Height: _____ cm	0 BMI < 19	1 BMI = 19-20	2 BMI = 21-22	3 BMI ≥ 23
2) Mid-arm circumference (MAC) in cm _____	0 MAC < 21	0.5 MAC ≤ 22	1 MAC > 22	
3) Calf circumference (CC) in cm _____	0 CC < 31	1 CC ≥ 31		
4) Weight loss (last three months)	0 loss > 3Kg	1 does not know	2 loss between 1-3Kg	3 no weight loss

B) General Assessment

D7) General Assessment

5) Lives independently (not in a nursing home or hospital)			0 no	1 yes
6) Takes more than 3 prescription drugs per day			0 yes	1 no
7) Has suffered psychological stress or acute disease in the past 3 months			0 yes	2 no
8) Mobility	0 bed or chair bound	1 able to get out of bed/chair but does not go out	2 goes out	
9) Neuropsychological problems	0 severe dementia or depression	1 mild dementia	2 no psychological problems	
10) Pressure sores or skin ulcers			0 yes	1 no

C) Dietary Assessment

11) How many full meals does the patient eat daily?			
0 1 meal		1 2 meals	
2 3 meals			
12) Consumes:		at least 1 serving of dairy products (milk, cheese, yogurt) per day	
Points if: 1 yes 0 2 yes 0.5 3 yes 1		2 or more servings of legumes or eggs per week	
		meat, fish or poultry every day	
		yes no	
		yes no	
13) Consumes 2 or more servings of fruits or vegetables per day?		0 no	
		1 yes	
14) Has food intake declined over the past 3 months due to loss of appetite?		0 severe loss of appetite	
		1 moderate loss of appetite	
		2 no loss of appetite	
15) How much fluids consumed per day?		0 less than 5 glasses	
		0.5 5 to 9 glasses	
		1 more than 9 glasses	
16) Mode of feeding		0 with assistance	
		1 self-feed with some difficulty	
		2 self-feed without any problem	

D) Self Assessment

17) Do they view themselves as having nutritional problems?	0 major malnutrition	1 does not know	2 no nutritional problems	
18) In comparison with other people of same age, how they consider their health status?	0 not as good	0.5 does not know	1 as good	2 better
			TOTALE (max 30 punti)	
MALNUTRITION INDICATOR SCORE: ≥ 24 = well-nourished, 17-23.5 = at risk of malnutrition, < 17 = malnourished				

* Vellas B et al. The Mini Nutritional Assessment (MNA) and its use in grading the nutritional state of elderly patients. *Nutrition* 1999; 15: 116-22.

CUMULATIVE ILLNESS RATING SCALE (C.I.R.S.) *

	NONE	MILD	MODERATE	SEVERE	EXTREMELY SEVERE
1. Cardiac (heart only)	1	2	3	4	5
2. Hypertension (rating is based on severity)	1	2	3	4	5
3. Vascular (arteries, veins, lymphatics)	1	2	3	4	5
4. Respiratory (lungs, bronchi, trachea)	1	2	3	4	5
5. EENT (eye, ear, nose, throat, larynx)	1	2	3	4	5
6. Upper GI (esophagus, stomach, duodenum, biliary and pancreatic trees)	1	2	3	4	5
7. Lower GI (intestines, hernias)	1	2	3	4	5
8. Hepatic (liver only)	1	2	3	4	5
9. Renal (kidneys only)	1	2	3	4	5
10. Other GU (ureters, bladder, urethra, prostate, genitals)	1	2	3	4	5
11. Musculo-skeletal-integumentary (muscles, bone, skin)	1	2	3	4	5
12. Neurological (brain, spinal cord, nerves)	1	2	3	4	5
13. Endocrine-metabolic (including diabetes, hyperlipidemia, infections, toxicity)	1	2	3	4	5
14. Psychiatric (dementia, depression, anxiety, agitation, psychosis)	1	2	3	4	5

ILLNESS SEVERITY SCORE (CIRS-IS) mean of all single item (excluded the psychiatric item)	COMORBIDITY INDEX (CIRS-CI) number of items with a score of 3 or greater (excluded the psychiatric item)
_____	_____

* Conwell Y, Forbes NT, Cox C, Caine ED. Validation of a measure of physical illness burden at autopsy: the Cumulative Illness Rating Scale. *J Am Geriatr Soc* 1993; 41: 38-41.

MULTIDIMENSIONAL PROGNOSTIC INDEX (MPI) *

CO-HABITATION STATUS

Does the patient live:	
Alone	
With relatives/nourse	
In institution	

MEDICATION USE

Number of drugs used	
-----------------------------	--

* Pilotto A, Ferrucci L, Franceschi M et al. Development and validation of a Multidimensional Prognostic Index for 1-Year Mortality from a Comprehensive Geriatric Assessment in Hospitalized Older Patients. *Rejuvenation Res* 2008;11:151-161.

Normogram for the calculation of knee height	HEIGHT (m)	Men (18-59 years)	1.94	1.93	1.92	1.91	1.90	1.89	1.88	1.87	1.865	1.86	1.85	1.84	1.83	1.82	1.81
		Men (60-90 years)	1.94	1.93	1.92	1.91	1.90	1.89	1.88	1.87	1.86	1.85	1.84	1.83	1.82	1.81	1.80
		Knee height (cm)	65	64.5	64	63.5	63	62.5	62	61.5	61	60.5	60	59.5	59	58.5	58
	HEIGHT (m)	Women (18-59 years)	1.89	1.88	1.875	1.87	1.86	1.85	1.84	1.83	1.82	1.81	1.80	1.79	1.78	1.77	1.76
		Women (60-90 years)	1.86	1.85	1.84	1.835	1.83	1.82	1.81	1.80	1.79	1.78	1.77	1.76	1.75	1.74	1.73
	HEIGHT (m)	Men (18-59 years)	1.80	1.79	1.78	1.77	1.76	1.75	1.74	1.73	1.72	1.71	1.705	1.70	1.69	1.68	1.67
		Men (60-90 years)	1.79	1.78	1.77	1.76	1.74	1.73	1.72	1.71	1.70	1.69	1.68	1.67	1.66	1.65	1.64
		Knee height (cm)	57.5	57	56.5	56	55.5	55	54.5	54	53.5	53	52.5	52	51.5	51	50.5
	HEIGHT (m)	Women (18-59 years)	1.75	1.74	1.735	1.73	1.72	1.71	1.70	1.69	1.68	1.67	1.66	1.65	1.64	1.63	1.62
		Women (60-90 years)	1.72	1.71	1.70	1.69	1.68	1.67	1.66	1.65	1.64	1.63	1.625	1.62	1.61	1.60	1.59
	HEIGHT (m)	Men (18-59 years)	1.66	1.65	1.64	1.63	1.62	1.61	1.60	1.59	1.58	1.57	1.56	1.555	1.55	1.54	1.53
		Men (60-90 years)	1.63	1.62	1.61	1.60	1.59	1.58	1.57	1.56	1.55	1.54	1.53	1.52	1.51	1.49	1.48
		Knee height (cm)	50	49.5	49	48.5	48	47.5	47	46.5	46	45.5	45	44.5	44	43.5	43
	HEIGHT (m)	Women (18-59 years)	1.61	1.60	1.59	1.585	1.58	1.57	1.56	1.55	1.54	1.53	1.52	1.51	1.50	1.49	1.48
		Women (60-90 years)	1.58	1.57	1.56	1.55	1.54	1.53	1.52	1.51	1.50	1.49	1.48	1.47	1.46	1.45	1.44

MPI - Multidimensional Prognostic Index

	Score given to each domain		
	Low (Value = 0)	Middle (Value = 0.5)	High (Value = 1)
SPMSQ ^a	0-3	4-7	8-10
ESS ^b	16-20	10-15	5-9
ADL ^c	6-5	4-3	2-0
IADL ^c	8-6	5-4	3-0
CIRS ^d	0	1-2	≥ 3
MNA ^e	≥ 24	17 to 23.5	<17
Number of drugs	0-3	4-6	≥ 7
Social status	Lives with family	Institutionalized	Living alone
Add up the scores assigned to each domain, and then divide the sum by 8			TOTAL SCORE

Legend:

RISK	Mild (MPI 1)	Moderate (MPI 2)	Severe (MPI 3)
RANGE	0.00 - 0.33	0.34-0.66	0.67-1.0
^a Number of errors ^b Exton Smith Scale Score: 16-20, minimum risk; 10-15, moderate risk; 5-9, high risk of developing ^c Number of active functional activities ^d Number of pathological (score > 3) ^e ≥ 24: satisfactory; 17-23.5: at risk of malnutrition; <17: Malnutrition			

Appendix B

TUG test

Timed Up and Go (TUG) Test

Name: _____ MR: _____ Date: _____

1. Equipment: arm chair, tape measure, tape, stop watch.
2. Begin the test with the subject sitting correctly (hips all of the way to the back of the seat) in a chair with arm rests. The chair should be stable and positioned such that it will not move when the subject moves from sit to stand. The subject is allowed to use the arm rests during the sit – stand and stand – sit movements.
3. Place a piece of tape or other marker on the floor 3 meters away from the chair so that it is easily seen by the subject.
4. Instructions: “On the word GO you will stand up, walk to the line on the floor, turn around and walk back to the chair and sit down. Walk at your regular pace.
5. Start timing on the word “GO” and stop timing when the subject is seated again correctly in the chair with their back resting on the back of the chair.
6. The subject wears their regular footwear, may use any gait aid that they normally use during ambulation, but may not be assisted by another person. There is no time limit. They may stop and rest (but not sit down) if they need to.
7. Normal healthy elderly usually complete the task in ten seconds or less. Very frail or weak elderly with poor mobility may take 2 minutes or more.
8. The subject should be given a practice trial that is not timed before testing.
9. Results correlate with gait speed, balance, functional level, the ability to go out, and can follow change over time.

Normative Reference Values by Age

Age Group	Time in Seconds (95% Confidence Interval)	
60 – 69 years	8.1	(7.1 – 9.0)
70 – 79 years	9.2	(8.2 – 10.2)
80 – 99 years	11.3	(10.0 – 12.7)

Cut-off Values Predictive of Falls by

Group	Time in Seconds
Community Dwelling Frail Older Adults	> 14 associated with high fall risk
Post-op hip fracture patients at time of discharge ³	> 24 predictive of falls within 6 months after hip fracture
Frail older adults	≥ 30 predictive of requiring assistive device for ambulation and being dependent in ADLs

Date	Time	Date	Time	Date	Time	Date	Time